AF INSTITUTE OF TECHNOLOGY

THE IDENTIFICATION AND FORECAST OF SEASONAL DEMAND CONSUMABLE ITEMS IN BASE SUPPLY

THESIS

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Mark Syzdek

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Abstract

This study investigated seasonally demanded consumable items at the base-level. This study examined how the Standard Base Supply System currently addresses seasonally demanded consumable items and some alternative methods of addressing consumable seasonal demand items in the SBSS. The alternative methods analyzed in depth were simple and Winters' seasonal exponential smoothing, and Box-Jenkins forecasting models.

This study found that items under study display some seasonal demand tendencies. The sample consisted of 12 out of 77 items identified as seasonal by Stock Control personnel at Langley AFB, VA. A graphical analysis showed stronger seasonal demand tendencies than did the autocorrelation function in which the correlations between demands one year apart are determined.

As was expected, the two seasonal models, Winters' exponential smoothing and Box-Jenkins better predicted demands for items under study than the SBSS model. Of 28 forecasts, Winters' exponential smoothing was best 13 times, while Box-Jenkins models were best 9 times.

The autocorrelation function could be used to test demand data for seasonality and flag items with seasonal demand patterns for special seasonal treatment, but this is not currently practical. Any useful effort to test all

items loaded on the SBSS at a base would require demand data for each item for four or, preferably, more years. Any manual attempts to test items for seasonality would be impractical given the number of items in the average base supply account.

Among the recommendations given as a result of this study is the suggestion that additional work be done to facilitate basing demand forecasts on seasonal models where appropriate.

THE IDENTIFICATION AND FORECASTING OF SEASONAL DEMAND CONSUMABLE ITEMS IN BASE SUPPLY

I. Introduction

General Issue

In 1985, Headquarters Tactical Air Command Supply personnel identified to the Air Force Logistics Management Center the need "to develop an automated method to identify seasonal items "(1). In the Standard Base Supply System (SBSS), there is no method to identify consumable items with seasonal demand patterns (1). This inability to determine periods of high and low demands leads to excessive inventories of items during periods of low demand and stockouts during periods of high demand (1). While a method exists in the supply system to load special stockage levels for seasonal items, no automated system is available to identify those items or the appropriate special levels (1).

Specific Problem

At the base-level, managers are forced to use guesswork and personalized attention to forecast demand and ensure availability of seasonally demanded items. In this context, seasonal items are considered items with demand patterns of three or more consecutive months' demand exceeding one standard deviation from the mean demand. Once an item is identified as seasonal, managers must also determine the appropriate stockage level for the item.

Research Questions

The following areas were addressed to determine if an automated system of forecasting range and depth of consumable seasonal demand items (what items to handle as seasonal and how many of those items to stock) can be developed for the SBSS:

1. How does the SBSS currently address consumable seasonal demand items?

2. What are alternative methods of addressing consumable seasonal demand items in the SBSS?

3. Do items currently identified as seasonal by personnel at the base-level actually display seasonal tendencies?

4. Can demand for the items currently identified as seasonal by personnel at the base-level be better forecast using a model that incorporates seasonal demand pattern information, or the current SBSS model?

5. What method could be used by personnel at the base-level to identify items as seasonal and forecast demands for those items accordingly?

Scope

This research effort concentrates on consumable items (also known as consumption items)

> which are either consumed in use or which lose their original identity during periods of use by incorporation into or attachments upon another assembly. Consumption items are issued on an as required basis and consist of such supplies as maintenance parts, raw materiel, office or house-keeping supplies consumed in use, and other similar items. (9:158-159)

Consumable items generally are more economical to replace than to repair. (Parkas, non-consumable items, are included in this study because they were included in the sample of seasonal items by the test base.)

Since the SBSS maintains limited demand data, the research is limited to one base which contributes to the Air Force Logistics Management Center's (AFLMC) database. Initially three of the twelve contributing bases were selected according to several criteria: 1) their location in an area with four distinct seasons, 2) being in different major commands, and 3) participating in the AFLMC database. The bases selected as potential candidates were Minot Air Force Base, ND, of the Strategic Air Command, Dover Air Force Base, DE, of the Military Airlift Command, and Langley Air Force Base, VA, of the Tactical Air Command. Because of the effort involved in extracting data from the AFLMC database it was decided to limit the study to only one base, Langley AFB, VA.

Summary and Overview

This chapter presented the problem of a lack of a systematic method for identifying seasonal items in the base supply system. The chapter also described the specific problem, reviewed the research questions, and delineated the scope of the research. The next chapter will cover the requirements computation and demand forecasting processes of the SBSS. In addition, a brief overview of several forecasting methods will be presented. The second chapter concludes with a survey of previous studies in this area. Chapter Three continues by detailing the research methodology. Chapter Four presents the results and analysis of the data collected. Finally, Chapter Five gives the conclusions and recommendations derived from the research.

II. Literature Review

Introduction

The United States Air Force is one of the largest buyers of goods and materials in the world. In consumable items alone, over 519,000 different items are stocked in the AFLC inventory for support of weapons systems (10). With such large purchasing needs lies the inherent responsibility to manage assets in an "effective and efficient" manner (8:2-45).

Once an item is purchased, it is either used or held in inventory until needed or deemed excess to requirements. As Ammer notes, inventories act as a hedge against uncertainties in supply and demand (2:257). He also notes that with

> too little inventory . . . manufacturing [or purchasing] efficiency and customer relations are bound to be hurt. Stockouts of essential materials mean some interruption of production [or readiness], which raises costs . . . . [In contrast, too much inventory will] tie up a company's capital: they generate storage costs; and deteriorate or become obsolete in storage. (2:255-256)

Standard Base Supply System Requirements Computations

At the base, or retail, level the SBSS is a computerized system designed to monitor inventories of spare parts, equipment and goods (8:1-5). According to Patterson, Seppanen described the SBSS "as a multi-item, single echelon, continuous review inventory system with stochastic, multiple unit demands, backordering and an annual budget constraint"

(23:1). This means the system manages a multitude of items at a single (base) level, and has continuous knowledge of stock levels. The system also assumes demand is stochastic. It permits backorders, and allows demands for multiple units, all subject to a budget constraint. Patterson also observed that the daily demand rate (DDR) "is the forecast measurement for the SBSS. Unless accurate estimates are available for the DDR considerable errors may result" (23:3). Thus, a critical function of the base supply system is to forecast demands to determine the quantity of each item to hold at the base-level. The DDR, or estimated demand, is the backbone of the entire SBSS stockage policy.

For years, logisticians, both civilian and military, have been trying to predict demand based on historical data. As early as 1962, Solomon noted that demand for Navy aircraft parts was exceedingly "low and sporadic," making forecasting difficult (28:55). In light of this, the SBSS' method of determining forecasts is discussed, along with how those forecasts are used. A brief survey of other forecasting methods will follow. Finally, a close examination of two powerful forecasting methods, exponential smoothing and the Box-Jenkins methodology will ensue.

<u>Demand Forecasting in the SBSS</u>. As was mentioned previously, demand computations are a critical component in the calculation of stockage requirements. The DDR is used to determine both the quantity to stock and which items to stock (23:1). First the calculations involved in

determining the quantity to stock will be presented. The USAF Supply Manual states that consumable item demand levels "are based on an economic order policy that balances the cost to order with cost to hold" (8:19-15). For a given item, the demand level is calculated from the sum of the "economic order quantity (EOQ), order and shipping time (O&ST) quantity, safety level quantity (SLQ), and a 0.999 rounding factor" (8:19-15). The demand levels are updated quarterly, for stocked items, in order to compensate for any changes in observed demand (8:19-11).

Daily Demand Rate. Common to the calculation of the EOQ, O&ST quantity, and SLQ is the daily demand rate (DDR). The daily demand rate formula is:

$$DDR = \frac{\text{Cumulative Recurring Demands}}{\text{Current Date - Date of First Demand}} \qquad [1]$$

(8:19-51)

The actual forecasting technique is more complex than first appears from this formula, since both the Date of First Demand (DOFD) and Cumulative Recurring Demands (CRD) are updated periodically. The CRD is simply a counter that records the number of total demands for the item. It is increased by the number of units ordered for each demand (23:2). In addition, the denominator in [1] is replaced with 180 (six months in days) when less than 180 days of demand history (current date - DOFD) is available. This assures that new items are not overstocked (23:2). Two additional adjustments are made every six months. The CRD is updated to the current DDR times the lesser of the difference between the current date and DOFD, or 365 (23:2). Also, the DOFD is adjusted to be the maximum of the DOFD or the difference between the current date and 365 (23:2). The net result of these adjustments is that the item's DDR is based on up to 540 days of demand history, (23:3) and that the forecasting model becomes "a modified exponential smoothing [model] with a changing smoothing parameter" (23:3). The exponential smoothing model is presented in greater detail later in this paper.

Economic Order Quantity. The economic order quantity is a model that replaces stock in batch sized orders to minimize the sum of carrying cost (the cost to hold an item in inventory) and the ordering cost. The simple EOQ model requires several basic assumptions including (20:638):

1) The demand rate is fixed.
2) Backorders or shortages are not allowed.
3) Delivery occurs just as inventories are depleted.
4) The quantity ordered does not affect carrying and holding costs.
5) Item cost is fixed.
6) Orders of one item do not affect another item's ordering or holding costs.

The simple EOQ formula then, is:

$$Q=(2DC_o/C_h)^{\frac{1}{2}} \qquad [2]$$

(20:643)

where Q is the optimal order quantity, D is the annual demand, C_o is the cost to place an order, and C_h is the cost to hold one unit of the item in stock for one year. Holding cost. C_h is usually expressed as a percentage of the cost of the item (20:643). So, the EOQ is based on four factors: the cost to order the item, the cost to hold the item in inventory, the annual demand for the item, and the purchase price of the item (8:19-15).

Air Force SBSS stockage policy sets the cost to order at two values depending on the source of the item. For items centrally procured from the depot supply system the cost to order is set at $5.20 (8:19-15). For local purchase items it is $19.94 because of the added costs of contracting to buy the item on the local market (8:19-15). The cost to hold one unit in stock for one year is set at 15% of the item's purchase cost (8:19-15).

This leads to the actual SBSS EOQ formula. Since the cost to hold and cost to order are assumed constant for both purchase cost categories, two formulas are used, one for centrally procured items and one for local purchase items:

$$\text{EOQ(Nonlocal Purchase)} = [8.3 *(\text{DDR} * 365 * \text{Unit Price})^{1/2}]/\text{Unit Price} \quad [3]$$
(8:19-52)

$$\text{EOQ(Local Purchase)} = [16.3 *(\text{DDR} * 365 * \text{Unit Price})^{1/2}]/\text{Unit Price} \quad [4]$$
(8:19-52)

The EOQ is not used in the strictest sense, however, since Air Force stockage policy dictates that the EOQ value must fall between 30 times the DDR and 365 times the DDR (8:19-52). So, at times, the exact EOQ quantity may not be ordered. In addition to the EOQ formula, however, several other quantities must be computed before determining the total quantity to stock of an item.

Order and Ship Time Quantity. The first of these other quantities is the order and ship time quantity. This is simply the product of the DDR and the average shipping time in days between the source of supply and the base (8:19-53). This value gives the quantity to stock to compensate for demands during shipment time from the depot.

Safety Level Quantity. The second quantity is the safety level, or the amount of stock held to compensate for variations in both lead time demand and order and shipping times. First the statistical variance of demand (VOD) and the variance of order and shipping time (VOO) must be calculated. To understand the following formulas, and their terms, several ideas must be introduced. The VOD is straightforward: it is simply a measure of how much lead time demand may vary over time for the item. The VOO, however, is calculated for all items coming from a given source of supply. For each receipt of an item from the source of supply, the time it took to receive the item is recorded. For example, if it took an item 12 days to arrive, then the counter for arrivals in 1 to 15 days (a delivery time segment) for that source of supply would be increased by one. Then a recalculation according to the following formulas would occur:

$$\text{VOD} = \frac{\Sigma(\text{Demand}^2) - \dfrac{(\Sigma \text{Demand})^2}{n_1}}{n_1} \qquad [5]\ (8{:}19\text{–}53)$$

$$\text{VOO} = \frac{\Sigma FI*MI^2 - \dfrac{(\Sigma FI*MI)^2}{n_2}}{n_2} \qquad [6]\ (8{:}19\text{–}53)$$

where n_1 is the maximum of either the number of days from the first demand or 180, n_2 is the number of receipts of the item for the period under consideration, FI is the number of receipts for a particular delivery time segment coming from a given source of supply, and MI is the midpoint of the delivery time segment days allowed for shipping for a particular priority coming from a given source (8 for the time segment 1-15 days) (8:19-53). The VOD is calculated during the requirements computation each time an item is demanded or quarterly during file status. The VOO is calculated quarterly for items with 100 or more receipts. These values are then used in the formula

$$\text{SLQ} = C * (\text{O\&ST} * \text{VOD} + \text{DDR}^2 * \text{VOO})^{1/2} \qquad [7]\ (8{:}19\text{–}53)$$

where C is a multiplier which increases the safety level of stocks according to the perceived criticality of the unit's mission and SLQ is the safety level quantity, the amount of stock to hold to prevent stockouts due to variations in shipping time and lead time demand. (O&ST as used in this equation is the mean of historical O&ST's recorded for items with a particular priority coming from a given source of supply.)

<u>Economic Order Quantity Demand Level</u>. Once the necessary parameters are calculated, the economic order quantity demand level may be calculated as follows:

$$EOQDL = TRUNC\,[EOQ + O\&STQ + SLQ + .999] \qquad [8]$$

(8:19-52)

where TRUNC means only the integer portion of the number is retained and the .999 serves as a round up factor. The EOQDL may be considered the amount of stock to hold which minimizes cost of holding and ordering while limiting stock-outs due to fluctuations in shipping time and lead-time demand.

Thus, as equations 3, 4, 5, and 7 show, the daily demand rate (estimated demand) is the backbone of the entire SBSS stockage policy. Blazer noted that "The forecast for demand is the biggest factor in determining the depth of stock" (4:1). It appears in the basic EOQ formula, the order and ship time calculation, and the safety level computation. Substantial errors in this value would certainly lead to potentially costly errors in stockage levels, either in terms of monetary expenditures or mission support.

Forecasting Methods

Because of the importance of the demand forecast, the methods by which this value can be determined must be examined. A number of methods of forecasting demand are available. Fildes divides them into three major categories:

> The judgmental--where individual opinions are processed, perhaps in a complicated fashion.
>
> The extrapolative--where forecasts are made for a particular variable using only that variable's past history. The patterns identified in the past are assumed to hold over to the future[.]
>
> The casual (or structural)--where an attempt is made to identify relationships between variables that have held in the past, for example, volume of brand sales and that product's relative price. The relationships are then assumed to hold into the future. (11:92)

Judgmental Forecasts. Fildes divides judgmental forecasts into three categories: individual, committee and Delphi forecasts (11:93). Individual forecasts are made when a single person forms an opinion on future demand based on experience and familiarity with the current situation (11:93). Committee or survey forecasts may be thought of as occurring when a group of people, either management or customers, form an opinion on future demand based on their perceptions (11:93). The Delphi method uses special techniques to combine the ideas of several people, but gives the individuals feedback without allowing one person's ideas to dominate the decision process (11:93).

Extrapolative Forecasts. According to Fildes, extrapolative forecasts come in five basic forms (11:94). The first is trend curve analysis, the method of fitting past demand data to a linear, exponential, or an S-curved function of time. A second form is decomposition, where a time series is broken into (1) its long-term trend, (2) its cyclical component--long-term swings about the trend, (3) its seasonal component--regular periodic fluctuations in demand, and (4) its random component--unpredictable fluctuations. Other extrapolative forecasts are exponential smoothing (a method "based on the weighted sum of past observations"), and Box-Jenkins (a systematic approach that finds the best particular method and weighted sums of a choice of models) (11:94). The final approaches are Bayesian methods that permit human intervention in a modified exponential smoothing method to account for known changes in the environment (11:94).

Causal and Structural Models. The last group of forecasting methods Fildes mentions are the causal models (11:95). These methods are generally more sophisticated and data intensive.

Fildes identifies a number of basic causal forecasting methods: regression, simultaneous systems, simulation, input-output, and cross-impact analysis (11:95). The first method, regression, involves finding a relationship between demand and some independent variable presumed to cause the demand (11:95). Related to this method are simultaneous system models which predict several dependent variables from several independent variables (11:95). The third modeling technique is simulation. Simulation models are more concerned with relationships and less concerned with strict mathematical analysis (11:95). Another type of model is the input-output model which capitalizes the fact that for a given output, a certain input must be available (11:95). Once the output is known the input level can be obtained. The final model is called cross-impact analysis (11:95). Its rationale is that demands are based on the occurrence of certain events. If the probabilities of those events occurring can be estimated, then demands can be forecast. This type of analysis can be carried out through several layers of events and probabilities (11:95).

Model Summary. The choice of which method should be used in a given circumstance depends on numerous factors. In fact, "no one method can be relied on to produce the 'best' forecasts in all circumstances" (11:96). Table 1 gives Fildes' opinion of the relative strengths and weaknesses of the different methods. Fildes judges each forecasting method according to seven parameters: (1) the relative number of data points required to use the method (DATA); (2) the statistical basis of the method, is it intuitive or not? (BASIS); (3) the difficulty of setting up the method (SET-UP); (4) the relative ease of using the method (EASE); (5) the comprehensibility of the method--how readily managers can understand the intricacies of the method (COMP.); (6) the assessability of the method--how easily the model can be evaluated, a measure of how specific the model is (ASSES.); and (7) the reported effectiveness--how much the model has been compared to and evaluated against other models in the literature (EFFECT).

Table I. An Evaluation of Various Forecasting Procedures

METHOD	DATA	BASIS	SET-UP	EASE	COMP.	ASSES.	EFFECT
JUDGMENTAL							
INDIVIDUAL	0	0	0	0	4	2	4
COMMITTEE	0	1	1	0	4	1	2
DELPHI	0	1	2	0	4	1	2
EXTRAPOLATIVE							
TREND CURVES	2	2	1	1	4	4	3
DECOMPOSITION	2	1	2	1	3	4	3
EXPONENTIAL SMOOTHING	1	1	1	1	3	4	3
BOX-JENKINS	3	3	3	2	1	4	4
BAYESIAN	1	2	3	2	1	4	1
CAUSAL							
SINGLE EQN	3	3	3	2	2	4	3
SIMULTANEOUS SYSTEM	4	4	4	4	1	4	2
SIMULATION	2-4	2	4	2	2	2	1
INPUT-OUTPUT	4	3	4	2	1	4	1
CROSS-IMPACT	1	3	4	3	2	1	1

("0" is low, and "4" is high)

Adapted from (11:100)

Time Series

Time series analysis uses past data to predict the future (29:41). By determining how the data changed over time in the past, the future may be predicted (29:41). Data behavior may be broken into five interacting components: "*levels, trends, seasonal variations, cyclical variations, and random variations*"(29:41). These are illustrated in Figure 1. The first component is the level component. This is the "central tendency of a time series at any given time"(29:41). The trend is the smooth line that represents

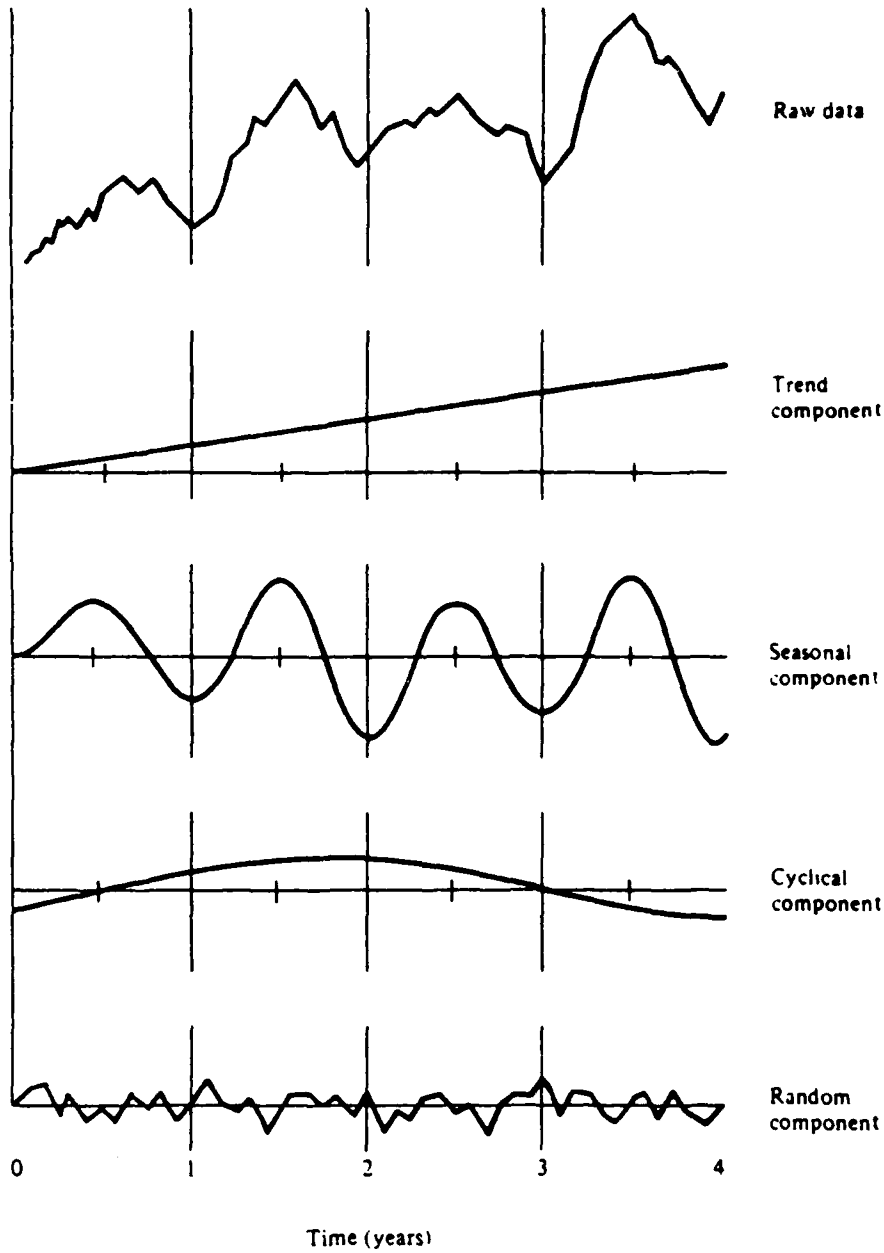

Figure 1. Time Series Components (29:42)

the long term pattern of the series (29:41). (It should be noted that trend and level components are essentially mutually exclusive.) Seasonal variations are fluctuations above and below the trend or level line which repeat from season to season. Normally thought of as being annual, some seasons are weekly or even daily. Cyclical variations are those that occur over longer time periods than seasonal variations and tend to be less consistent (29:41). They could be construed to be related to long-term business cycles if appropriate. Random variations are those in the data which cannot be accounted for otherwise and have no identifiable pattern.

Exponential Smoothing

Of the various forecasting techniques, exponential smoothing offers one of the best combinations of accuracy and low data processing and retention requirements. This conclusion is supported in full by the literature. Brown comments that accuracy, simplicity of computation, and flexibility to adjust the rate of response were three of the most "frequently important" criteria of a forecasting method and noted that exponential smoothing benefited from these qualities (6:91). Peterson and Silver point out that because of the limited data and calculation requirements of simple exponential smoothing models they are well suited to handling thousands of items (25:111). Tersine notes "the major advantage of [simple exponential smoothing] is that the effect of all previous data is included in the previous forecast figure, so only one number needs to be retained to represent the demand history" (29:53). Blazer notes that "time series models are the most practical models for forecasting Air Force EOQ items," making special mention of single (or simple) exponential smoothing (4:22). In fact, Patterson notes that the SBSS uses a modified exponential smoothing model (23:3). Since exponential smoothing is considered so useful, a more detailed explanation of how it works is in order.

Moving Averages. Many derivations of the exponential smoothing formula use moving averages as a starting point (6; 18; 30). The bases of moving averages and exponential smoothing are lacking in statistical rigor (30:55), but they are still very useful and intuitively valid in spite of their lack of a rigorous mathematical foundation. The idea behind moving averages is to forecast based on an average of recent actual data (30:55). The average of a predetermined number of recent data points is used to forecast the next period's demand. The average "moves" because as newer data become available, the oldest data points are eliminated from consideration; thus, the forecast reflects only the most recent values (30:55). The moving averages formula is:

$$F_{t+1} = (X_t + X_{t-1} + \ldots + X_{t-N+1})/N \qquad [9]$$

$$= \left(\sum_{i=t-N+1}^{t} X_i\right)/N \qquad [10]$$

or

$$= [(X_t) - 1 \; (X_{t-N+1})]/N + F_t \qquad [11]$$
(18:47-48)

where N is the number of periods in the forecast, X is the demand in a period, F is the forecast for a period, t is the current period, and t+1 is the next period.

It is apparent from these formulas that the greater the value of N, the more stable the forecast. The smaller the value of N, the faster the forecast reacts to changes (18:46). In other words, a large value of N would be appropriate for forecasting stable demand with relatively large random fluctuations, because the forecast would not follow the random variations, but would smooth the fluctuations. In contrast, a small value of N would react quickly to changes in demand and follow changes in demand quickly. In both cases, moving averages forecasts would tend to lag or follow the demand pattern (18:46).

According to Meredith, however, exponential smoothing has two major advantages over moving averages: smaller data requirements and greater ease of computation (20:91). Yet, exponential smoothing balances the need to smooth the forecasts with a number of periods of historical data, and the need to forecast new trends with recent data.

Exponential Smoothing. The basic formula for exponential smoothing can be developed from [11]. Assuming the value of X_{t-N+1} is unavailable, a reasonable approximation for stationary data would be F_t, the forecast for the previous period. Substituting into [11] results in

$$F_{t+1} = X_t/N - F_t/N + F_t \qquad [12]\ (18:49)$$

Equation 12 can be rewritten as

$$F_{t+1} = (1/N)X_t + (1-1/N)F_t \qquad [13]\ (18:49)$$

This results in a forecast derived from weighting X_t (the most recent data point) with 1/N and weighting F_t (the most recent forecast) with 1-1/N. Substituting a smoothing coefficient, α, for 1/N, where $0 \leq \alpha \leq 1$, [14] becomes

$$F_{t+1} = (\alpha)X_t + (1-\alpha)F_t \qquad [14]\ (18:49)$$

Seppanen, referenced by Patterson, observes that in the SBSS $\alpha = N/(365+N)$ for recent demands where N is the number of days since the last semiannual adjustment (23:3). Exponential smoothing's reduced data storage requirements can be readily seen: only the most recent demand, the most recent forecast and α must be retained. Rewriting [14] yields

$$F_{t+1} = F_t + \alpha(X_t - F_t) \qquad [15]\ (18:50)$$

or

$$F_{t+1} = F_t + \alpha e_t \qquad [16]\ (18:50)$$

where e_t is the forecast error for period t. So, the new forecast for period t + 1 is actually the previous period's forecast plus a fraction of the error between forecast and demand. Intuitively, this seems appropriate that a good estimator of the future would be the last forecast plus a portion of the error in making that forecast (18:48-50).

Exponential Smoothing with Seasonal Factor. Winters (one of the original developers of exponential smoothing) expanded the usefulness of the model by incorporating a seasonal demand factor. He started by assuming that any seasonality was proportional to the demand of that period rather than being additive, or independent of demand (32:327). The first equation of the Winters' model can be expressed as:

$$S_t = (\alpha)X_t/I_{t-L} + (1-\alpha)F_{t-1} \tag{17}$$
(32:328)

where L is the number of periods in one seasonal cycle, (for example, for a yearly cycle L would be 12) and S_t is the "estimate of the expected deseasonalized sales rate in period *t*" (32:328). The estimated seasonal factor for the period t, I_t, can be calculated using

$$I_t = (\beta)X_t/S_t + (1-\beta)I_{t-L} \tag{18}$$
(32:328)

where β is the seasonal smoothing factor, which must be chosen empirically. The seasonal factor, I_t, is chosen so that like periods are forecast; the last corresponding period must be used in the calculations. For example, one must use last year's June I_t value to make this year's June forecast (32:328). The actual forecast is made using:

$$F_{t+M} = S_t * I_{t-L+M} \tag{19}$$
(32:328)

where M is the number of periods into the future to forecast (32:327-329).

<u>Exponential Smoothing with Trend and Seasonal Factors</u>. The previous model does not, however, compensate for any type of trend. Winters also developed a trend and seasonal model where:

$$S_t = (\alpha)X_t/I_{t-L} + (1-\alpha)(F_{t-1} + b_{t-1}) \qquad [20]$$
(32:329; 18:72)

The b_{t-1} factor accounts for an additive trend. The seasonal factor remains unchanged from [18]:

$$I_t = (\beta)X_t/S_t + (1-\beta)I_{t-L} \qquad [21]$$
(32:330; 18:72)

The trend factor resembles [19] and [20] in its structure: (32:330)

$$b_t = (\Gamma)(S_t-S_{t-1}) + (1-\Gamma)b_{t-1} \qquad [22]$$
(32:330; 18:72)

The smoothing constant, Γ, must be chosen arbitrarily. The final forecast becomes

$$F_{t+M} = (S_t+b_t{*}M){*}I_{t-L+M} \qquad [23]$$
(32:330; 18:73)

To obtain a forecast using either of these methods, S_t is first calculated using I_{t-1} because I_t cannot be determined until S_t is calculated. Then I_t and b_t, if required, can be obtained. Finally F_{t+M} can be found from [19] or [23] (32:329-330; 18:72-73).

Useful as Winters' method is, it has one major drawback: "it requires three smoothing parameters" (18:79).

This greatly increases the data requirements and computer time required to generate forecasts. In response to this concern, Zehna and Taylor noted as long ago as 1975 that computer processing times should not "be a significant factor in the selection of forecasting techniques" because of the great increases in computer power and speed (33:38). Ammer adds that in general:

> Exponential smoothing is not a perfect technique for forecasting demand. Like other statistical techniques, it is based on past demand and obviously cannot allow for new and unpredicted changes in demand. In addition, it may help increase inventories because . . . small shifts in weekly demand can be magnified into substantial shifts in order points when trend is taken into account. Despite its weaknesses, however, exponential smoothing is an excellent technique, especially when used in conjunction with electronic data processing to control order points of thousands of low-value C items. (2:305)

Box-Jenkins

A more sophisticated methodology for forecasting which may outperform exponential smoothing was developed by Box and Jenkins to create a class of forecast models known as ARIMA models. This method is based on two major premises (30:171). First, the data are assumed to be in the form of a time series, in which observations are taken over a period of time, and the forecast is needed for some future period in time (30:171-172). Second, the data are assumed to be following a pattern with an obscuring random component (30:171-172). The objective of the forecaster, then, is to identify the pattern and use it to make forecasts (30:171-172).

Box-Jenkins can be considered a process. The following iterative procedure, diagrammed in Figure 2, is recommended by Box and Jenkins to develop a forecast (5:19). The essential idea is that an initial class of model is selected based on certain factors (to be discussed in greater detail later), and a model is tentatively identified (5:18). The model parameters are then estimated and the model is evaluated against certain diagnostic checks (5:19). Based on the evaluation, either the model is used, or another model is tested (5:19). Eventually, a model meeting the diagnostic requirements is developed and the model is selected to make forecasts (5:19).

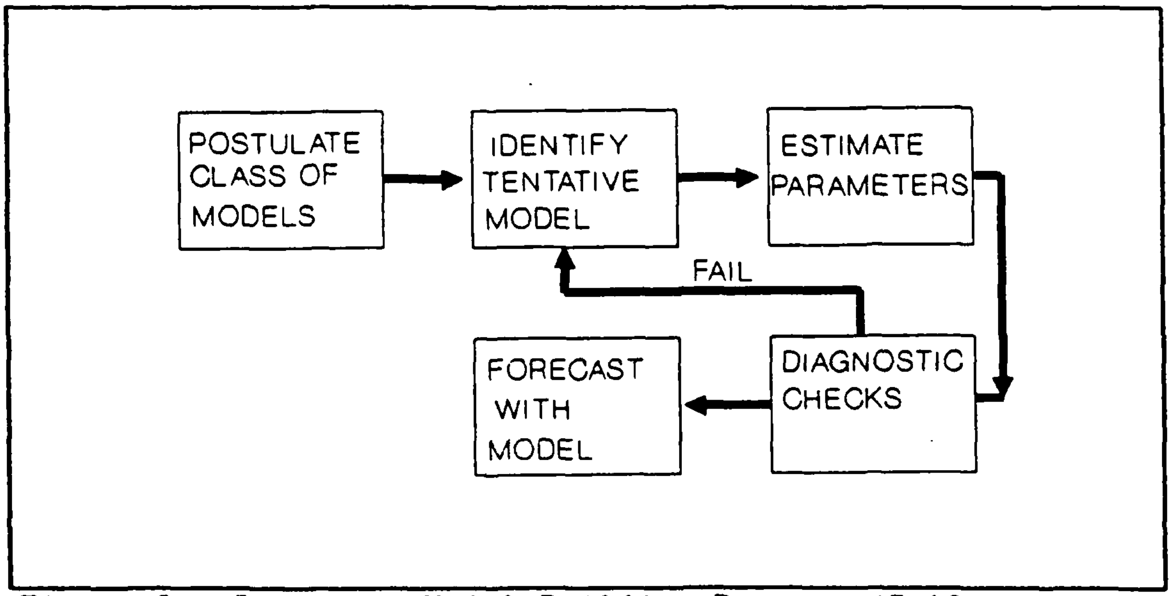

Figure 2. Iterative Model Building Process (5:19)

The Box-Jenkins methodology incorporates two major types of models which together make up the class of autoregressive integrated moving average processes (ARIMA processes) (5:8). In order to better understand the terminology involved, the backshift operator is first defined as

$$Bz_t = z_{t-1} \qquad [24] \; (5:8)$$

The more general case is

$$B^m z_t = z_{t-m} \qquad [25] \; (5:8)$$

Another important operator is the backward difference operator, δ, which may be defined by the following equation:

$$\delta z_t = (1-B)z_t = z_t - z_{t-1} \qquad [26] \; (5:8)$$

These operators are computational artifacts which make the mathematical analysis more straightforward and permit the simplification of a number of equations.

<u>Autoregressive Models</u>. A very useful model in the Box-Jenkins methodology with practical applications is the autoregressive model. In this model the "current value of the process" is a function of the previous values of the process and some additional factor or shock, a_t (5:9). If the values of the process at times t, t-1, t-2 . . . are represented by z_t, z_{t-1}, z_{t-2} . . . then $\tilde{z}_t$, $\tilde{z}_{t-1}$, $\tilde{z}_{t-2}$ can be the differences of each z_t from the mean μ, as in $\tilde{z}_t = z_t - \mu$. Then

$$\tilde{z}_t = \phi_1 \tilde{z}_{t-1} + \phi_2 \tilde{z}_{t-2} + \quad . \; . \; . \quad + \phi_p \tilde{z}_{t-p} + a_t \qquad [27]\ (5:9)$$

is an autoregressive (AR) process of order p. Using the autoregressive operator of order p

$$\phi B = 1 - \phi_1 B - \phi_2 B^2 - \; . \; . \; . \; . \; - \phi_p B^p \qquad [28]\ (5:9)$$

the AR model may be written

$$\phi(B)\tilde{z}_t = a_t \qquad [29]\ (5:9)$$

or

$$\tilde{z}_t = \psi(B) a_t \qquad [30]\ (5:9)$$

where

$$\psi(B) = \phi^{-1}(B) \qquad [31]\ (5:10)$$

<u>Moving Average Models</u>. A second model, the moving average process, is based on the a_t's, the error terms. A moving average (MA) process of order q may be written

$$\tilde{z}_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \; . \; . \; . \; . \; - \theta_q a_{t-q} \qquad [32]\ (5:10)$$

If a moving average operator is defined as

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \; . \; . \; . \; . \; - \theta_q B^q \qquad [33]\ (5:10)$$

then the MA model simplifies to

$$\tilde{z}_t = \theta(B) a_t \qquad [34]\ (5:10)$$

or

$$a_t = \tilde{z}_t(1 - \theta B)^{-1} \qquad [35]\ (5:10)$$

or

$$a_t = \tilde{z}_t \pi \qquad [36]\ (5:50)$$

where

$$\pi(B) = (1-\theta B)^{-1} \qquad [37]\ (5:50)$$

Autoregressive - Moving Average Models. If the data support it, a combination of AR and MA terms is necessary. The ARMA model is simply an AR and an MA model combined. It may be written as follows:

$$\tilde{z}_t = \phi_1 z_{t-1} + \ldots + \phi_p \tilde{z}_{t-p} + a_t - \theta_1 a_{t-1} - \ldots - \theta_q a_{t-q} \qquad [38]\ (5:11)$$

or in shorthand

$$\phi(B) z_t = \theta(B) a_t \qquad [39]\ (5:11)$$

Although the AR. MA, or combined models suit stationary time series (those that vary about a constant mean), frequently the data call for a non-stationary model that will account for changes in the mean of the process. By introducing the "generalized autoregressive operator" $\varphi(B)$ and the stationary operator, $\phi(B)$, for the AR process, one can write (5:11)

$$\varphi(B) z_t = \phi(B)(1-B)^d z_t = \theta(B) a_t \qquad [40]\ (5:11)$$

where the term (1-B) accomplishes the differencing. In other words, an ARMA process is differenced by creating a new series with the differences between the value of one period and the value of the previous period. The new series is a more generalized model. This gives a general model

$$\phi(B)w_t = \theta(B)a_t \tag*{[41] (5:11)}$$

where

$$w_t = \delta^d z_t \tag*{[42] (5:11)}$$

Thus, by taking d differences of the process to make it stationary, nonstationary behavior may be modeled. This last process described is called an autoregressive integrated moving average (ARIMA) process of order (p, d, q) (5:11).

Figure 3 illustrates how the ARIMA process "filters" random errors through the three operations to yield the time series.

Seasonality. One major characteristic of a seasonal time series is that every s (for annual seasonality of monthly data, s = 12) periods a similar observation may be made. Another characteristic is that successive months (in the case of annual seasonality) will also be similar. For example, an observation made in October will be similar to one made the previous October and all other October observations. Additionally, the October observation will be similar to September's and November's observations for the same year. (5:303-304)

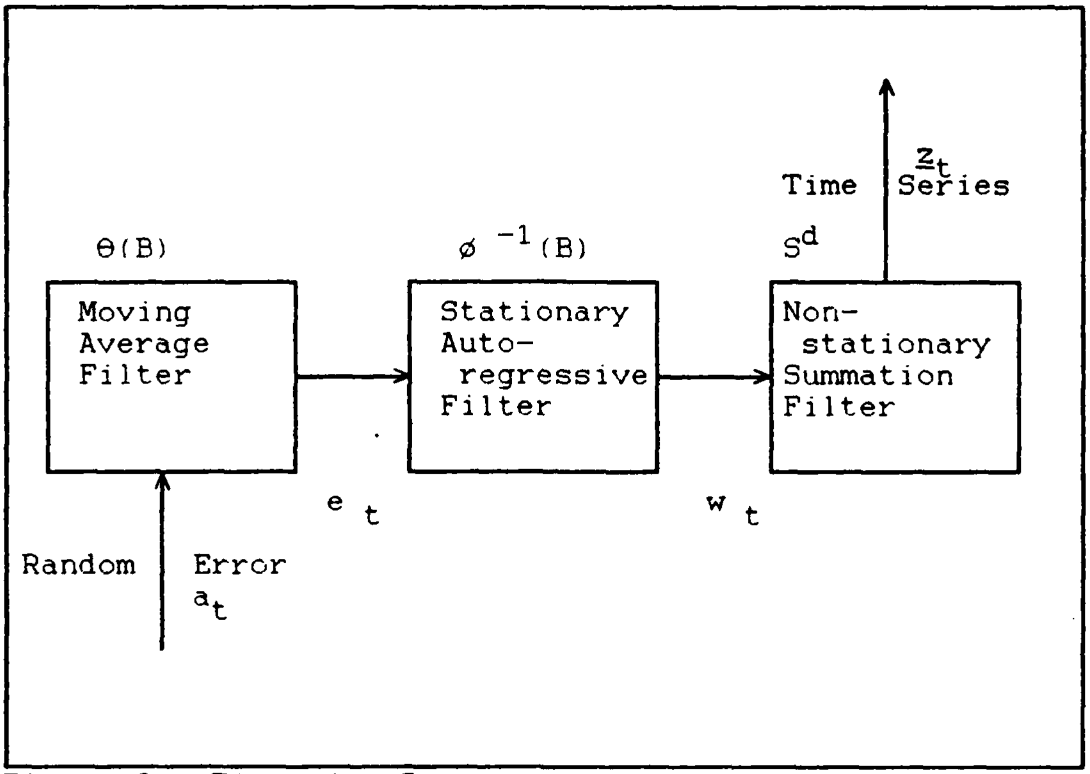

Figure 3. Filtering Process to Convert White Noise to Time Series (5:12)

A model of the form

$$\Phi(B^s)\delta_s^D z_t = \Theta(B^s)\alpha_t \qquad [43]\ (5:304)$$

may be written where $s = 12$, $\delta_s = 1 - B^s$, and $\Phi(B^s)$ and $\Theta(B^s)$ "are polynomials in B^s of degrees P and Q, respectively, and satisfying stationarity and invertibility conditions" (5:304). A stationary model randomly varies about one mean (5:7) and has the condition that $\psi(B)$ is within the range -1 to +1 (5:51). An invertible model is slightly more difficult to explain. Because the moving average model depends on the error terms for its value of z_t, if the absolute values of the individual Θ's are greater than one, the weights of the a_t's will increase, leading to a nonstationary condition (5:50). Thus the condition of invertibility is imposed, that the sum of the $\theta^i B^j = \pi(B)$ is within the range -1 to +1 (5:51).

Having defined and described Box-Jenkins models the methodology behind applying them will be discussed in Chapter 3.

Previous Studies

The management of seasonal items has received much attention in the literature (6; 21; 25; 29; 30), although few military studies have been done. One of these was the Air Force Institute of Technology thesis by Gilloth, Ohl, and Wells in 1979 titled "An Evaluation of Seasonality in the United States Air Force Medical Material Management System" (MMMS) (14). After examining the demand patterns of 1886 items (14:36), they determined that seasonality was evident in 25 - 35% of the medical supplies examined, while only about 8 - 9% of the items were seasonal over both the years tested. They concluded that double exponential smoothing was the best forecasting method tested, using mean squared error as the selection criteria (14:28,58). Other forecasting methods examined were the current MMMS system (12 month moving average), and adaptive response rate exponential smoothing (a method in which the smoothing constant is automatically varied as the demand pattern changes) (14:43). One of their recommendations was for increased data retention to benefit future studies, since they only had two years of non-consecutive data with which to work (14:59). This lack of data limited considerably the generalizability of their research (14:20).

Other studies include one done by Orchowsky in 1985 on clothing items, in which some items investigated showed seasonal demands, but most items did not (22:30-31). This study examined 4563 individual national stock numbers, managed by the Defense Logistics Agency, which were grouped into 300 Procurement Grouping Codes (PGC) (22:3). (A PGC is a group of like clothing items differentiated only by size (22:3)). Orchowsky used the autocorrelation function (ACF) for 12 lags to determine if a random or seasonal pattern existed (22:10). Briefly "the ACF is a measure of the relationship (correlation) of the time series with itself, lagged by some number of time periods" (22:10). For example data points, taken monthly, 12 periods apart, with a high autocorrelation would indicate a strong correspondence on a seasonal basis--seasonal data.

Fischer and Gibson, in 1971, examined single, double (with a trend) and triple (with a quadratic component) exponential smoothing and a 12 month moving average (12:9). Their sample consisted of 34 EOQ items from Wright-Patterson AFB Base Supply. Fischer and Gibson were disappointed in the performance of triple exponential smoothing, expecting it to perform better than it did (12:67). They concluded that an inadequate database, with only 22 months of data available, prevented the determination of acceptable smoothing constants (12:71). The smoothing constants were "optimized" by testing several values for the minimum sum of squared errors (12:45). Statistically, the four models had the same mean square error, with or without "optimized" smoothing constants (12:49).

A fourth study, undertaken by Bittel and Gartner in 1982, examined demand for consumable items at the depot level (3). Their analysis of 800 line items (3:42) used the following models (3:56):

1. Naive (the next period forecast is the last period's actual value)

2. Simple moving average (4, 8, and 12 periods)

3. Double moving average (4, 8, and 12 periods)

4. Single exponential smoothing (α=0.2 and 0.8)

5. Focus forecasting (a "multi-model technique which employs simplistic forecasting assumptions and computer simulation to forecast demand" (3:49-50))

6. Simple regression (a method of fitting the line with the least mean squared error to the data)

7. S-curve analysis (a model used to describe and "estimate the life cycle of technologies and products. An S-curve has a slow start, a rather steep growth, and a saturation that comes after some period of time" (19:169))

8. Exponential growth (a model which describes constant growth rates over long periods of time (19:171))

9. Eclectic forecasting (similar to focus forecasting, but uses more complex techniques (3:50))

Although Bittel and Gartner were looking at a different echelon of demand, they noted that simple exponential smoothing gave the lowest mean average deviation and variance of all the methods tested. However, they observed that the method was statistically equivalent to single [sic] moving averages with four and eight month periods (3:79). Additionally, they noted that the data "showed some normal demand patterns with considerable random variation" (3:75).

Another study which indirectly examined seasonality was one by Gertcher in 1982 (13). As part of his research into different methods of forecasting demand for consumable items, he used triple exponential smoothing, which assumes a quadratic shape to a plot of the historical demand data (13:20). His major difficulties in using triple exponential smoothing were poor initialization constants and the lack of fit of the demand data to the assumed second order polynomial (13:44). In other words, the data did not fully exhibit the quadratic pattern of the model he was using.

The consensus of most of these studies is summed up in a study on demand variance by Blazer, who noted that the nemesis of the analysis of competing forecasting methods is a lack of sufficient demand data (4:3). He notes that 10 years of data is desirable. Yet Gilloth, Ohl, and Wells used data from calendar years 1975 and 1977 (14:20); Orchowsky was able to obtain 33 months of data (22:2); Zehna and Taylor had only 8 quarters of data (33:22). Each of these efforts suffered from the lack of data maintained by the SBSS.

Determination of Seasonality

Peckham gives three criteria for manually determining if seasonal trends exist:

(1) The peak demand should be substantially higher than the random fluctuations or "noise" in the demand.

(2) The peak demand must occur during the same time period each year.

(3) The reason for the peak must be known. (25:40-41)

Based on this, a plot of the data would frequently give an indication of whether or not an item exhibited seasonal demands. A strong indication of seasonality would be a pattern of demands generally repeating itself over several years, with peaks and valleys being considered significant if greater than two standard deviations from the mean demand. This would give the demand spikes a 4% chance of being considered significant when they actually were not, assuming a normal distribution of demands.

However, manually determining seasonality in this fashion does not lend itself to a statistically verifiable analysis. Without a definition of "substantially higher" different analysts may arrive at different conclusions regarding the same data. A method relying less on intuition, the ACF as used by Orchowsky (23), could be readily used to detect seasonality in data.

To better understand autocorrelation, simple correlation will be defined first, as in a discussion by Wheelwright and Makridakis (30:116). Simple correlation is a measure of the relationship between two variables. A correlation coefficient, r, which ranges from -1 to +1, is used to measure the strength of the relationship. With perfect correlation, r would be either ±1; with no correlation r would be 0. A value of +1 is assigned for a positive correlation, while a value of -1 is assigned for a negative correlation. In other words, r would be +1 between two identical sets of numbers, and -1 between a set of negative numbers and the absolute values of those same numbers. In addition, an r of 0 implies there is no relationship between the two variables, that is: they are completely independent and a change in one has absolutely no effect on the other. (30:116, 174)

An autocorrelation coefficient extends this same idea to "values of the same variable but at different time periods" (30:174). In this case, the data under consideration are made into several different data sets, each treated as a different variable. The first data set consists of the original data. The second data set is the same data, with the first value removed, and all others moved up one spot. Thus, the original value for period 1 is dropped, the original value for period 2 becomes the new value for period 1, the original value for period 3 becomes the new value for period 2 and so on. Then this new, second, data set is used to generate a third data set using the same principles. The second data set's value for period 1 is dropped, the second data set's value for period 2 becomes the newest value for period 1. the second data set's value for period 3 becomes the newest value for period 2 and so on. This is done as long as data is available to continue creating new data sets. (30:174-175)

Wheelwright and Makridakis continue by observing that each data set can now be considered a new variable, and a correlation coefficient can be calculated between each of the data sets (30:175). The correlation coefficient tells how data a certain number of time periods apart is correlated. The correlation between the original data set and the second data set shows how data one period (lag) apart are correlated and whether they tend to move in the same direction or not. The same can also be done with the rest of the data sets (30:175). The correlation between the original data and the lagged data is obtained. Since the correlation is between the data and itself, one or more periods removed, the correlations are called autocorrelations (30:175-176). The ACF is useful in identifying seasonal data because it can be used to identify at which lags the correlations are largest. If the ACF for the 12th lag for monthly data (data points 12 months apart) is statistically significant then the data can be reasonably presumed seasonal (30:176).

Forecast Performance Measures

A number of methods are available to determine how "good" a particular forecasting method is at forecasting.

The basic assumption of any forecasting technique is that there is a fundamental pattern to the observations, plus some random error or fluctuations. The object of forecasting then, is to minimize those errors. Error is usually defined as the difference between the actual value and the forecasted value.

A method of evaluating those errors is necessary. A simplistic method of analyzing error would be to average all the errors, but since positive and negative errors may cancel each other out, this could lead to an erroneous assumption that the overall errors are small. An improvement would be to average the absolute value of the errors, but this would weight all errors the same. Yet another alternative would be to average the squared errors. This more heavily penalizes large errors in favor of small ones. An error of 4 would be counted 16 times as much as an error of 1. This method, the Mean Squared Error (MSE), will be used in this study.

Conclusions

The SBSS has a sophisticated demand forecasting system designed to compute an average daily demand rate, which is used to establish stockage levels. The system can be thought of as a modified exponential smoothing model. An examination of a variety of forecasting methods revealed a number of potential forecasting methods. However, experts tend to agree that if many items' demand must be forecast, exponential smoothing has several advantages over other methods, especially its minimal computational and data storage requirements. Exponential smoothing is a very simple method of forecasting, although the addition of terms to compensate for trend and seasonality added considerable complexity to the model. In spite of this, exponential smoothing remains the model of choice for forecasting large numbers of items because of its modest requirements. The Box-Jenkins methodology is an powerful way of generating the best time series or ARIMA model to fit a given data set. Although relatively difficult to use, it offers confidence intervals for both parameters and estimates, in contrast with the intuitive exponential smoothing techniques. In addition, the Box-Jenkins methodology is quite data intensive.

Little military research has been performed in examining how well seasonal forecasting methods perform with consumable SBSS items. Previous studies that did attempt this had mixed success, primarily because of the lack of sufficient data.

The next chapter discusses how the actual research was conducted. It also describes how the data were obtained and analyzed.

III. Methodology

Introduction

This chapter discusses the data collected for the research and how it was obtained, manipulated, and finally used. The chapter also mentions the limitations and assumptions involved in the study. The actual research plan is highlighted along with details of the SBSS, Exponential Smoothing and Box-Jenkins methodologies.

Data Collection

Population and Sample. The population of interest is the entire set of consumable items used by the United States Air Force. The sample will consist of twelve out of 77 consumable items identified as seasonal by Langley AFB, VA, which are listed in Attachment 1. Only twelve items were selected for study because of the difficulty in extracting demand data from transaction history tapes.

The data are not generalizable to the entire population of Air Force bases because the selection of Langley as a study base was non-random. Demand patterns depend on a number of factors including how and when certain items are ordered at a facility, the weapons systems at the facility, the mission of the facility, and potentially its geographic location.

Assumptions. The following assumptions were made regarding this investigation:

1. Responses from the Stock Control Section at Langley AFB accurately reflect its situation.
2. Data transmitted to and from the Air Force Logistics Management Center (AFLMC) is accurate and complete.
3. Changes in the climatic environment of Langley AFB over the data history are such that they do not significantly impact the seasonality of the data.

Limitations. The following limitations are apparent in this investigation:

1. The limited number of both bases investigated and years of data do not permit generalizability of the results Air Force-wide.
2. Variations in the methods Langley AFB's Stock Control Section uses to determine which items are seasonal or not may make those items they determine to be seasonal unrepresentative of other bases.
3. No aircraft parts were identified as seasonal: only items such as cold weather gear and deicers were identified as seasonal.

Data Collection. The data came from two sources. First, Mr Almond, the Stock Control Officer at Langley AFB contributed a list of consumable items that the base considers seasonal. The purpose in obtaining this list was to determine if selected items on the list indeed hold seasonal characteristics in their demand patterns and to develop forecast models for selected items from the sample.

The second source of data was the database at AFLMC. This database was started to provide historical data beyond that normally held by the SBSS. The necessary data were extracted from two types of records: item records and transaction histories. Item records are the major record on each item that, together with detail records, collects the data required "to manage most items under nearly all circumstances" (8:4-84). Item records were obtained that reflect the end of March 1989. Transaction histories are a consolidated record of all transactions that affect the inventory of an item. Unfortunately transaction histories were only available for the dates marked by an X in Figure 4. The extracted data included national stock number; nomenclature; expendability; repairability; recoverability category code (ERRC); cumulative recurring demands; dates of first demands; and demands. The first three data sets are available from the item record.

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1982		X	X	X	X	X		X	X	X	X	X
1983	X	X		X	X	X	X		X	X	X	X
1986								X	X	X		
1987		X		X	X	X	X	X	X	X	X	X
1988		X	X	X	X	X	X	X	X	X	X	X
1989	X	X	X	X								

Figure 4. Data Available (X) from AFLMC

The demand data were obtained through analysis of the transaction histories for each item for the period of interest. A demand was considered to have occurred for every Document Identifier Code (DIC) of ISU (for issue) and DUO (for due-out) for the item. As a check of the ISU and DOR codes, Type Transaction Phrase and Codes (TTPC) were used (26). A TTPC code of "1A" which decreases the available quantity recorded under the item record detail, a code of "2D" which adds and increases the due-out detail, a code of "3Q" which indicates a post-post (computer off-line) issue were the codes considered to substantiate a request for an issue from stock (8:3-134-137).

Both mainframe and personal computers were used to extract the data. After the data were shipped from AFLMC on magnetic tape, they were loaded on the Air Force Institute of Technology's VAX mainframe computer. One of several FORTRAN programs were then used (an example is in Attachment 2) to extract only those stock numbers selected for further study and load the needed portions of the transaction records for each stock number into a separate file. Each file was then transferred via modem to a floppy diskette where it was accessible to an MS-DOS personal computer. Once on a diskette, each file was imported into Quattro, a spreadsheet program. Then the database management function of Quattro was used to extract only those records with either an ISU or DUO DIC code and with a transaction date within a given month. TTPC codes were manually verified along with the requested stock number to ensure the item requested was the item ordered. The number of units requested for each demand transaction were summed to give a final number of units demanded for each month for each stock number. This figure was hand-copied and subsequently verified. The resulting demands for the twelve stock numbers for each available month are listed in Attachment 3.

One problem with the data was the presence of a gap between December 1983 and August 1986. According to Mr. Miller of the AFLMC all of the data in the AFLMC database has a similar gap (varying in length at different bases) because of the installation of new base supply computer systems during that time period (21). He stated that the AFLMC has "given you everything we've got" (21). Because the Box-Jenkins methodology requires so much data, it would be impossible to develop any models on the relatively continuous August 1986 through April 1989 data.

To determine the feasibility of using data from before and after the gap the following procedure was used. The demand data from 1982 and 1983 for each stock number was compared to the same stock number's demand data from 1987, 1988, and 1989 to statistically determine if the two groups of data came from the same distribution. A Wilcoxon Signed Rank Test was used. This technique tests if two samples came from the same population distribution or not. The results of the test are in Table II. They indicate that only seven of the twelve items had demand data useable for

Table II. Wilcoxon Signed Rank Test Results for Similar Distributions

Wilcoxon Signed Rank Test Results

NSN	P-VALUE	SAME DISTRIBUTION YES/NO ?
1	.4902	YES
2	.0547	NO
3	.4885	YES
4	.0269	NO
5	.1814	YES
6	.0049	NO
7	.0461	NO
8	.0737	NO
9	.1052	YES
10	.4885	YES
11	.3816	YES
12	.5251	YES

the Box-Jenkins methodology with a 90% confidence level. If the P-value was greater than 0.1 then the null hypothesis that the two distributions were the same could not be rejected. For these seven items the 1982 and 1983 demand data were treated as if they came from the years 1985 and 1986. and combined with the 1987 and 1988 data. The 1989 demand data were used as a holdout sample for comparison purposes. Since the exponential smoothing techniques require less data, they were run using longest continuous string of data available: August 1987 through December 1988, with the 1989 demand data saved as a hold-out sample. Thus, the exponential smoothing forecasts are based on a slightly different database than the ARIMA forecasts.

Unfortunately, as was noted in Figure 4, the data was incomplete, and several months' data was lacking in addition to the 1983-1986 gap. This posed a severe problem for time series analysis since continuous data is essential to the methodology. Peterson and Silver note that "data will not always be available, [so one] must resort to asking knowledgeable persons to provide . . . guesstimates for the values of level, trend, and seasonal factors" (25:120). They additionally note that the forecasts obtained from incomplete data augmented by expert opinion must be carefully monitored and the forecasting model updated as new data becomes available.

To fill in the missing data points, a Delphi technique was used. This technique involves using experts to forecast when data is otherwise unavailable. The method starts with asking the experts to independently arrive at a forecast. Then the results from the first set of forecasts are summarized as a simple mean and range (the highest and lowest values) (17:23). Each expert is then asked if, based on the mean and range of the previous results, he or she desires to keep the same forecast or change it. Within three or four iterations, depending on the nature of the problem and the data, a consensus is arrived at and the experts no longer wish to change their forecasts (17:23).

In this study, five supply officers were asked to act as experts, evaluate the available data, and generate values for the missing data points using their knowledge of both the available demand data and forecasting techniques. Attachment 4 lists the demand data used in the exponential smoothing forecasts, while Figures 10-21 offer graphical representations of the same values. Similarly, Attachment 5 lists the demand data used in the Box-Jenkins forecasts, while Attachment 6 offers a graphical representation of the same values. The missing data points replaced by Delphi-generated values are underlined in Attachments 4 and 5. Recall that problems with obtaining complete data forced the use of slightly different data sets for the exponential smoothing forecasts and the Box-Jenkins forecasts. In addition, recall that the lack of complete data forced the use of only seven National Stock Numbers (NSN) for the Box-Jenkins forecasts.

Research Plan

The research questions were addressed in the following combination of consultation with experts, literature review, and analysis of existing data:

1. The methods by which the SBSS currently addresses consumable seasonal demand items were reported in the literature review.

2. Other methods that could be used in the SBSS to address consumable seasonal demand items were also identified and discussed in the literature review.

3. To determine if items currently identified as seasonal by personnel at the base-level actually display

seasonal tendencies. Stock Control personnel at Langley AFB were asked for a list of items that are given special management attention based on suspected seasonality. The demand histories of these items were evaluated to determine if, in fact, seasonal trends do exist in the data, using the autocorrelation function.

4. To determine if a seasonally adjusted exponential smoothing model, a simple exponential smoothing model, an ARIMA model, or the current SBSS model is the best method for forecasting demand for consumable seasonal demand items, the demand for the above items were forecasted using these four models by the following method.

Demand data, obtained from AFLMC, was divided into two parts. Three years of data was used to define the parameters of each model and predict the consumption of the item during the fourth year, which was used to test the models. The best model will have the lowest Mean Squared Error defined as the mean of the squared differences between each forecast and the corresponding actual demand, as determined by an ANOVA test for significant differences.

5. In order to identify a method that could be used by base-level personnel to identify seasonal items one major difficulty must be overcome. Vital to any system of identifying seasonal data are demand data collected over three preferably more years. Because of the number of items handled by the SBSS, the amount of demand data available is

limited. Therefore, the response to this research question is necessarily limited to recommendations in Chapter V.

Models

SBSS Forecasting Methodology. As was described in Chapter II, the daily demand rate is the SBSS demand forecast. Essentially a simple moving average forecast, it is recalculated as needed (26). Whenever a demand is made for an item in the SBSS, an R is placed in the requirements computation flag field of the item record (8:19-31). If a demand level has already been calculated that quarter, then requirements computation is performed. Requirements computation examines how many of the item are available, how many are needed, and whether more should be requisitioned or some should be returned as excess. If the demand level has not been recalculated for the item that quarter, then the demand level and date of last releveling would be updated (8:19-32). Thus, for each quarter, the demand level is calculated only once, although the daily demand rate is calculated whenever required by the SBSS (26).

For the comparison with exponential smoothing and Box-Jenkins, the DDR was calculated as follows. The SBSS calculates the DDR by dividing the CRD by the current date minus the DOFD, with several exceptions, as explained in Chapter 2 (see [1]). Two adjustments are made every six months. The CRD is updated to the current DDR times the lesser of the difference between the current date and DOFD, or 365 (23:2).

So, for items loaded on the base supply system for more than one year, the old CRD is changed to be the current DDR times 365. Also, the DOFD is adjusted to be the maximum of the DOFD or the difference between the current date and 365 (23:2). Thus, the DOFD is adjusted to be one year ago for all items in the system over a year.

The item records sent by AFLMC were from the end of March 1989, (Julian date 9090). Based on the items' DOFD of 8090 (365 days prior to 9090 day), the item records had been releveled just prior to being transmitted to AFLMC. The CRD field (obtained from the item record), divided by 365 equals the DDR. Also, the calculated DDR, multiplied by 540, gives the CRD after the releveling (new CRD). (According to Patterson 540 days are the *maximum number* of days in a demand history (23:4), although this is not exactly equal to 365 + 180). The actual demands placed on each item were also available so that past and future CRDs could be obtained. Thus, the DDRs both before and after the releveling could also be calculated from the CRDs.

A sample calculation (for NSN 1) will better illustrate how this was done. Some of the intermediate and final values in the calculation are given in Table III. The item record (new) CRD was divided by 365 to obtain the current DDR. Since the DDR before the releveling was the CRD divided by 540, the current DDR, .408, was multiplied by 540 to obtain 220, the old CRD. Then the number of demands occurring in March 1989, 10, was subtracted from this CRD to

Table III DDR Calculation Values

	DEC 88	JAN 89	FEB 89	MAR 89 OLD	MAR 89 NEW	APR 89
CRD	195	203	210	220	149	154
DDR	0.433	0.415	0.413	0.408	0.408	0.389
ACTUAL DEMAND	8	7	10	9	9	5
FCST	13.43	11.64	12.8	N/A	12.24	12.06

obtain 210, the CRD at the end of February 1989. This CRD was divided by 540 - 31 (the number of days of demand history, obtained by subtracting the number of days in March from the previous number of days demand history) to obtain the DDR at the end of February. Thus, the end of February DDR was multiplied by 31 to give the forecast for the month of March. January and December were handled the same way.

The calculation of the SBSS forecast for the month of April was more straightforward. For the April forecast, the new CRD was divided by 365 (the new current date - DOFD) and multiplied by 30. Although not used, the May forecast could be obtained by adding the known April demands to the new CRD and dividing the result by 365 + 30 to obtain the new DDR. This could be multiplied by 31 to obtain the May forecast.

Exponential Smoothing Methodology. The model building for the Winters and simple exponential smoothing models was accomplished using the commercially available MS-DOS program

Forecast Master. The program uses time series data to create models which it uses to generate forecasts.

Of the four exponential smoothing methods available, two, simple exponential smoothing and Winters exponential smoothing were used. Simple exponential smoothing was used as being somewhat comparable to the SBSS method. Both methods produce only a single value to be extended for all forecast periods. Winters' seasonal exponential smoothing models were chosen for comparison with ARIMA models because both compensate for seasonal effects.

The technique used by Forecast Master to generate forecasts is quite straightforward. The program selects the best model smoothing parameters as determined with an "iterative search method to minimize squared error over the historical data" (15:9-2). Each run was initialized with the same smoothing parameters to ensure consistency. For simple exponential smoothing α was set at 0.2. For Winters exponential smoothing α was also set at 0.2, β was set at 0.05, and Γ was set at 0.001. After the computer settled on a set of optimal parameters the parameter values were noted. The forecast generation process required several steps, one for each forecast. The first forecast was for the first four months of 1989, using data through December 1988. The second forecast was for February through April 1989 using data through January 1989, and so on. Thus, four separate sets of forecasts, each ending in April 1989 (the end of the holdout data), were made.

Box-Jenkins Methodology. The three major steps involved in the Box-Jenkins methodology include identifying a tentative model, estimating the parameter values and evaluating the model, and preparing a forecast.

Identifying a Tentative Model. The first step in building a Box-Jenkins model is to identify a tentative ARIMA model. As Box and Jenkins explain, model identification is an inexact science

> because the question of what types of models occur in practice and in what circumstances, is a property of the physical world and cannot, therefore, be decided by purely mathematical argument. (5:173)

The tentative model identified is only to be used if diagnostic tests demonstrate the model fits the data adequately.

The first part of the model identification process is to determine if differencing is necessary to make the data stationary. Nonstationarity is identified by autocorrelation functions that do not die off (become insignificant) but appear almost linear (5:174-175).

The second part of the process is to determine the orders, p and q, of the AR and MA processes. Here the autocorrelation function (ACF) and partial autocorrelation functions (PACF) are used. Before going any further, however, the partial autocorrelation function must be described.

This analysis is derived from that given by Goodrich and Stellwagon in their guidebook to the Scientific Systems forecasting program, Forecast Master (15:8-9,10). An AR process may be identified by its ACF. although p remains unknown. Since an AR process is essentially a regression equation. however. p may be determined as follows. Assume k to be the order of the regression equation

$$Y_t = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_k Y_{t-k} + e_t \qquad [44]$$
(15:8-10)

which can be written and the values of the α's determined. In addition. an equation with k+1 parameters may also be written

$$Y_t = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_{k+1} Y_{t-k-1} + e_t \qquad [45]$$
(15:8-10)

If α_k and not α_{k+1} is significant then it can be safely assumed that the proper order of the equation describing the data is k. The PACF is a function describing all the possible k's. (15:8-9.10)

If the autocorrelations decline exponentially to zero. then an AR model is likely to best explain the data. Likewise. if the partial autocorrelations decline exponentially to zero. then an MA model is appropriate. The PACF. then. will be zero for k greater than p and non-zero for k less than p. The order of the AR model. p. is determined by the number of "spikes" or significant partial autocorrelations. in the PACF. For example. two significant spikes indicate a p of two. (The ACF and PACF for a sample AR 2 model. in Figures 5 and 6. show significant spikes at lags 1. 2. 3. and 6. and at lags 1 and 2. respectively.) Similarly the order of the MA model. q. is determined by the number of

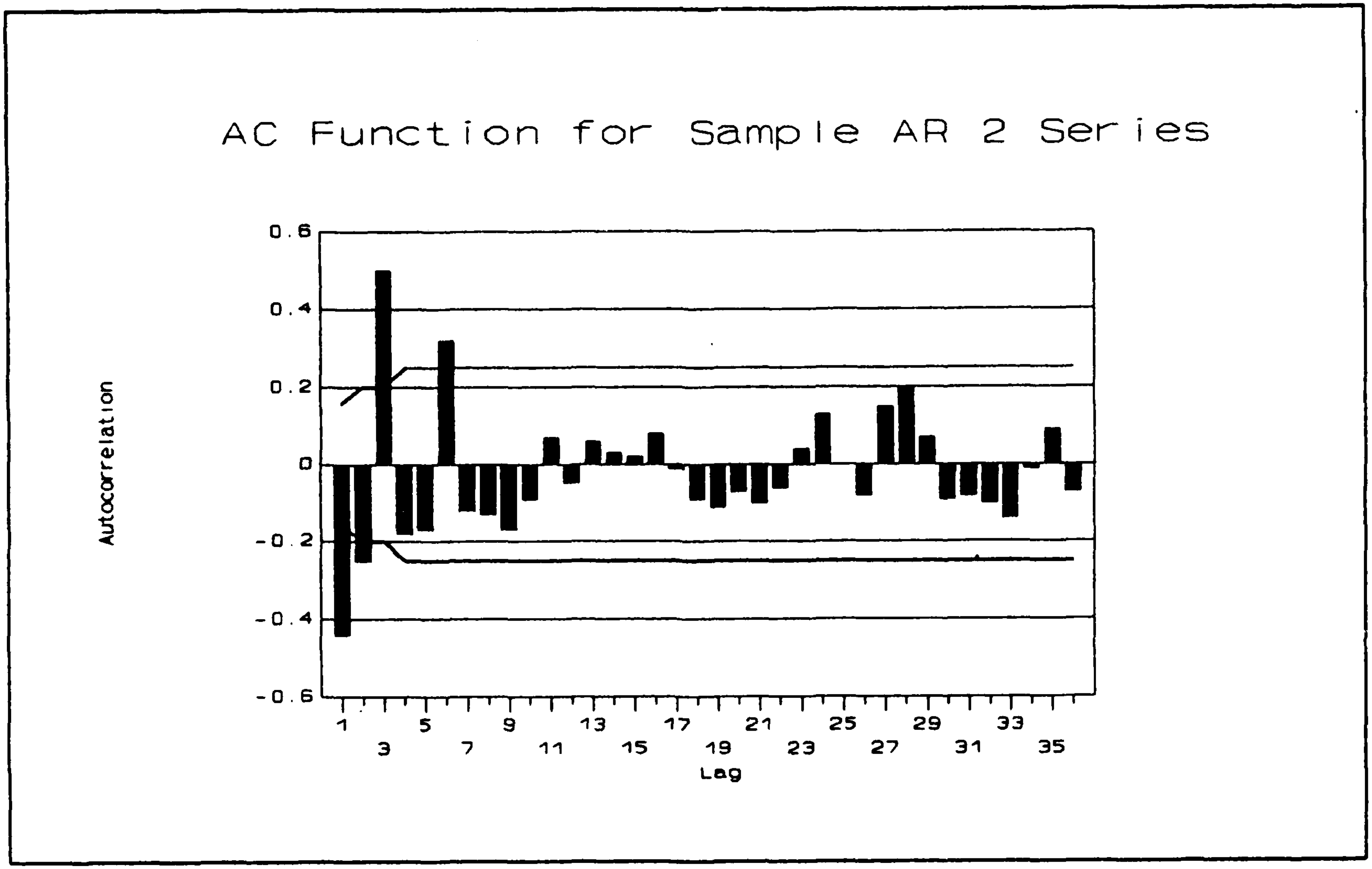

Figure 5. Autocorrelation Function for Sample AR 2 Series

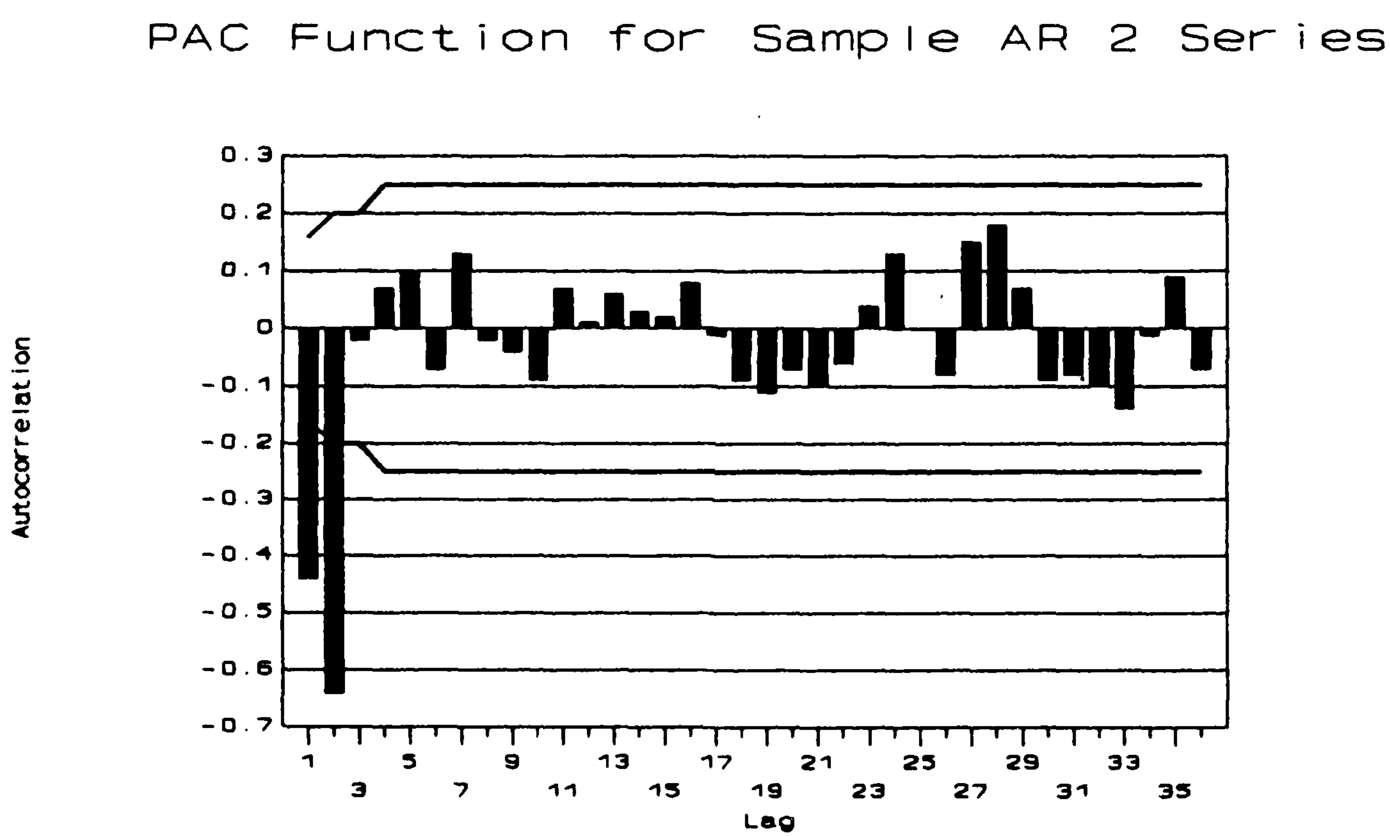

Figure 6. Partial Autocorrelation Function for Sample AR 2 Series

spikes in the ACF: two significant spikes is evidence of q equal to two. (The ACF and PACF for a sample MA 2 model, in Figures 7 and 8, show significant spikes at lags 1, and 2, and at lags 1, 2, 3 and 4, respectively.) (5:175-177; 15:8-10; 16:62-65)

Essentially the same process is used in identifying seasonal parameters, except the ACF and PACF's at lags 12, 24, and 36 are examined. An example of a seasonal pattern is presented in Figure 9. (Figure 9 shows significant spikes at lags 1, 11, 12, and 13, with the spike at lag 12 larger than those at lags 11 and 13). The number of data points available becomes critical in this area, because the identification of seasonality depends on several years of data. Also, judgement and simply trying various models become important analysis tools. (16:171-173)

Parameter Estimation and Model Evaluation. The next step in the Box-Jenkins methodology is that of estimating parameters and evaluating the model. The computer program, Times, performs the parameter estimation step using a nonlinear (Marquardt) routine which minimizes both "the relative error in the sum of squares" and the relative error in each parameter value (31:12).

A variety of diagnostic tools are available to the Box-Jenkins forecaster. The first of these is to check for correlations in the residuals. If the differences between the actual and predicted values are correlated then the model is not capturing all the underlying patterns (demand

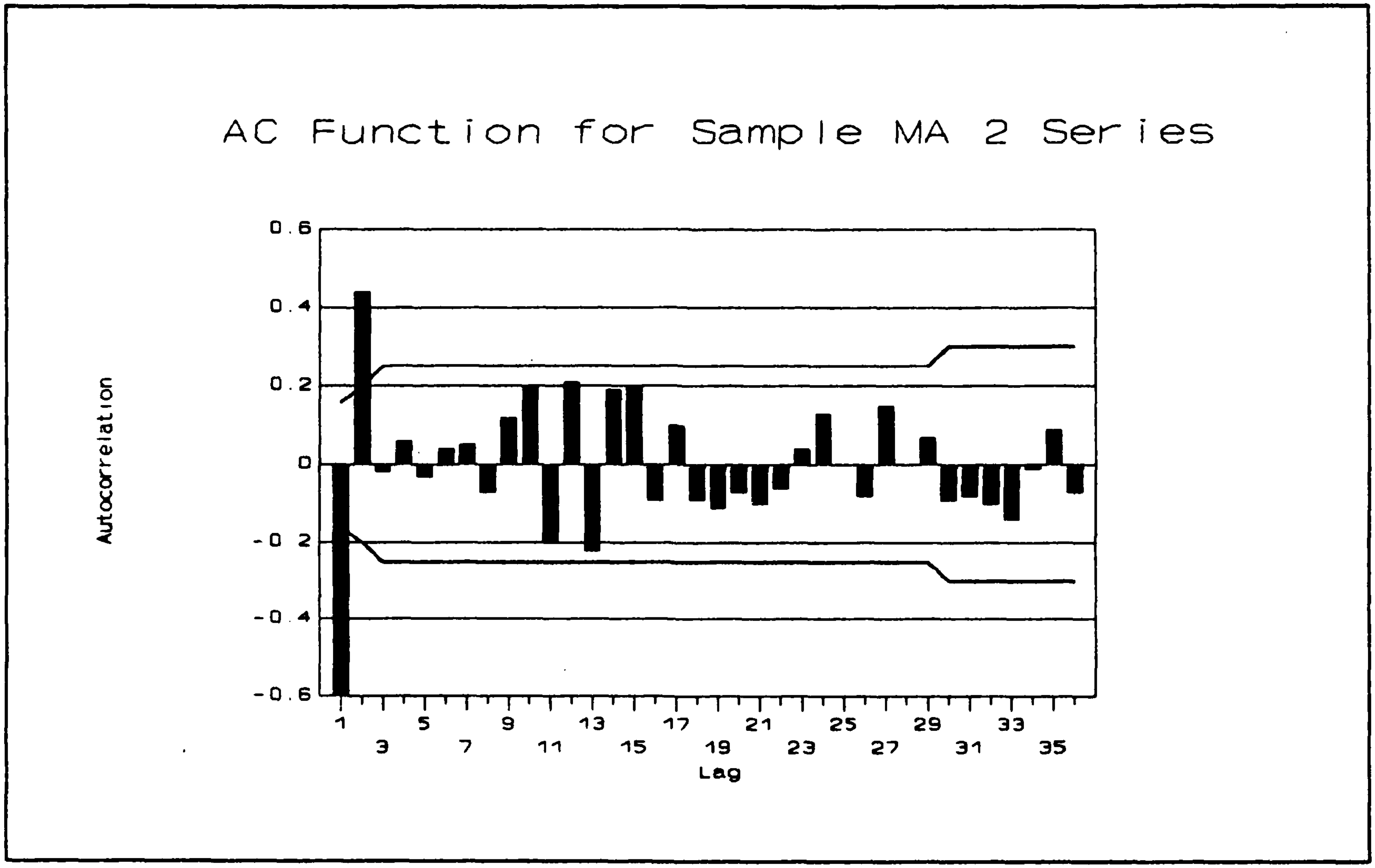

Figure 7. Autocorrelation Function for Sample MA 2 Series

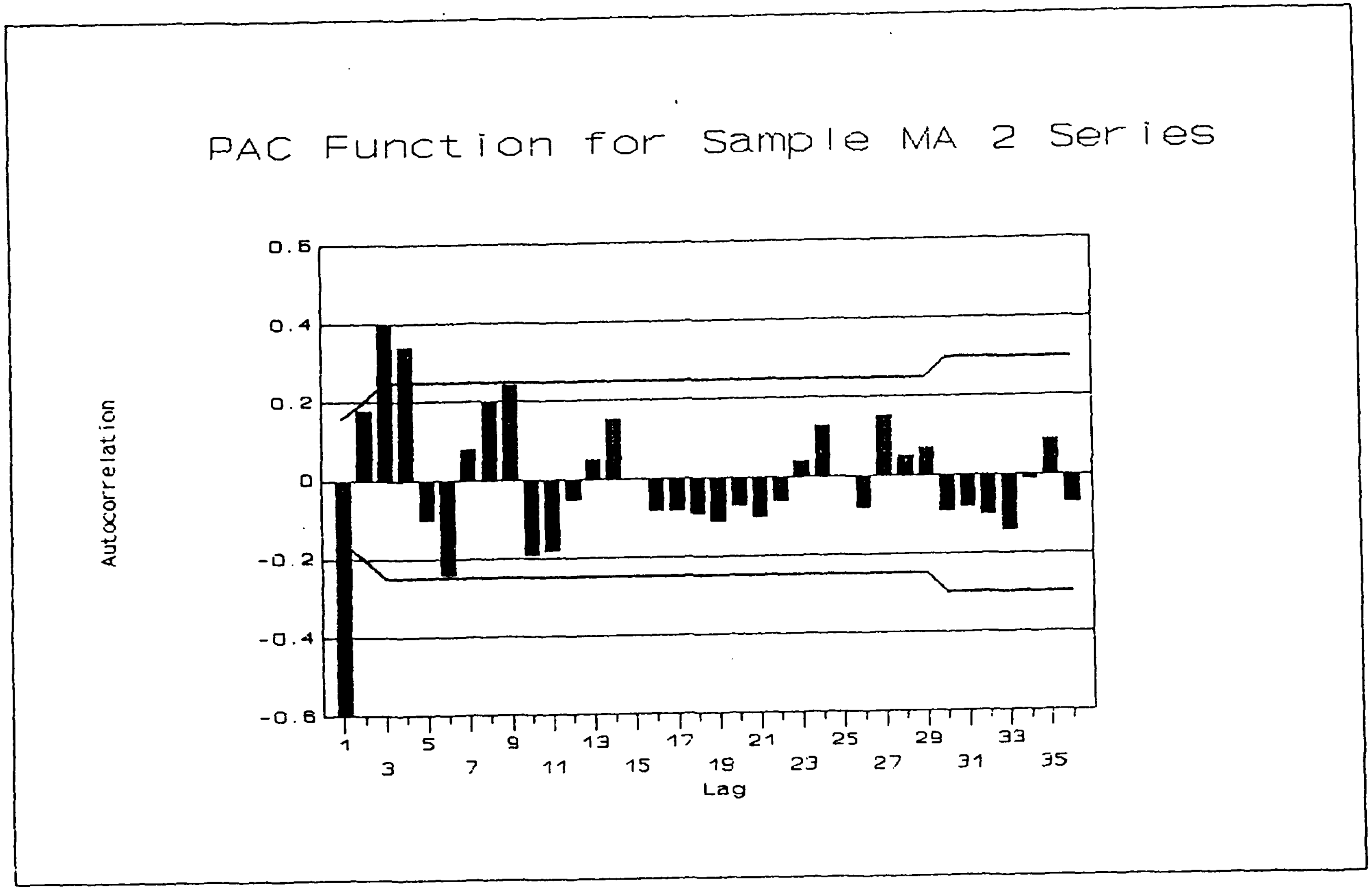

Figure 8. Partial Autocorrelation Function for Sample MA 2 Series

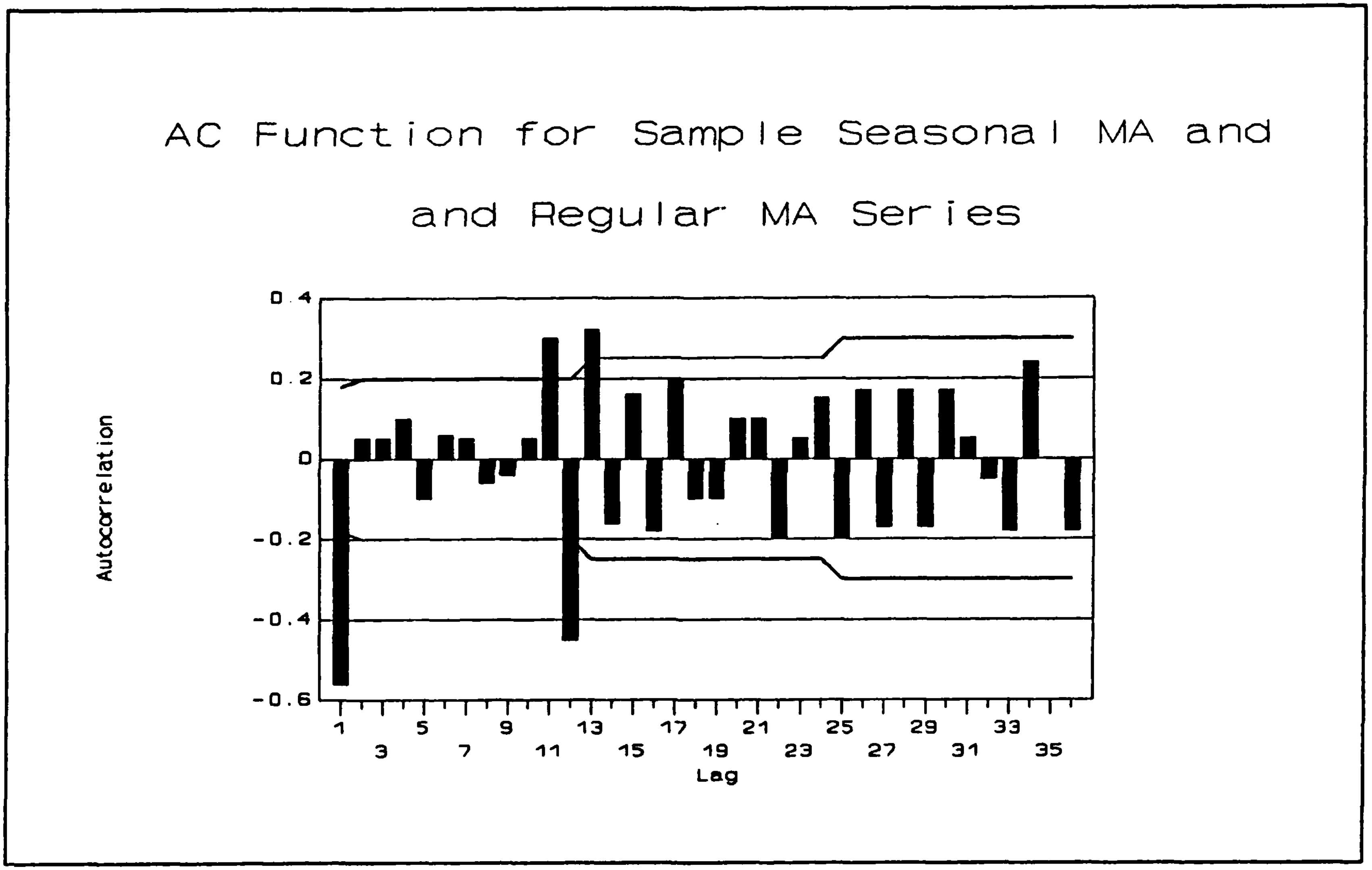

Figure 9. Autocorrelation Function for Sample Seasonal MA and Regular MA Series

information). Thus, the ACF of the residuals is examined for any significant spikes (16:91-92).

The second diagnostic tool is to plot both the residuals and their histogram. The residuals should have a somewhat normal distribution, be random (with no discernable pattern about the mean) and have a mean not significantly different from zero. According to Hoff, the last can be tested by determining whether or not the residual mean is greater than "2 times the residual standard error divided by the square root of the number of residuals" (16:91).

A third diagnostic tool is the Q-statistic (5:291-3). This is a check to see if a selected group of residuals resulted from a poor model: in other words, whether or not they are correlated as a group. If the first K autocorrelations are used in the formula

$$Q = n \sum_{k=1}^{K} r_k^2(\hat{a}) \qquad [46]$$

(5:291)

where n is the total number of observations minus the number of differences taken and r_k^2 is the residual autocorrelation, and Q is the Q-statistic. The Q-statistic is compared to a chi-squared distribution with (K-p-q) degrees of freedom. If the Q statistic is too large at the desired confidence level, then the model may be regarded as inadequate. (5:291-3)

Another diagnostic tool is the cumulative periodogram (5:294-295). This is a means of evaluating for periodic patterns that the ACF cannot readily detect. The periodogram function is defined as

$$I(f_i) = 2/n[(\sum_{t=1}^{n} a_t \cos 2\pi f_i t)^2 + (\sum_{t=1}^{n} a_t \sin 2\pi f_i t)^2 \qquad [47] \ (5{:}294)$$

where $f_i = i/n$ is the frequency. If the series in question is random, then the periodogram takes on the appearance of a straight line running from the coordinates (0,0) to (0.5,0). A sufficiently large deviation from this line is indicative of periodicity not captured by the model.

A model passing these basic tests may be considered adequate for the forecaster to move on to the final step: using the model to prepare forecasts. The process of generating forecasts is relatively straightforward. Once the parameters and form of the forecast model are known, the computer simply solves the equation to obtain the forecast.

Forecast Comparisons. Once forecasts were obtained from each forecast method, they were compared with the holdout sample from the first four months of 1989 (January 1989-April 1989). Each model was evaluated by MSE on how well it predicted the values in the holdout sample. The forecasts from each model were obtained four times and the number of times the model had the lowest MSE was recorded to indicate how successful each technique was at predicting the values in the holdout sample. The first forecast used demand data through December 1988 to forecast demands for January through April 1989. The second forecast used demand data through January 1989 to forecast demands for February through April 1989 and so on. Since only seven NSNs could be used to create ARIMA models because of the two year data gap problem, only those seven NSNs were used to compare all four models. The other five NSNs were not used in this evaluation step.

Summary

This chapter discussed the data acquisition and manipulation process. It also highlighted the methods used to actually make forecasts from each forecasting method and how those forecasts would be compared against the holdout sample. The next chapter continues with the results of the forecasts and how each model fared in predicting the holdout sample.

IV. Data Analysis and Results

Introduction

This chapter discusses the results of the data analysis and the relationships found during the study. First results of the seasonal tests will be discussed. Next, the exponential smoothing models will be discussed, followed by the ARIMA models. The relationships between the models of similar stock numbers will also be discussed. This will be followed by the results of the forecasts and the rating of each model on its performance in predicting the holdout data.

Seasonality Tests

Two methods of determining whether data is seasonal or not were mentioned in the previous chapter: examination of plots and evaluation of the autocorrelation function.

Demand Data Evaluation. First, data plots will be evaluated. Recall from Chapter III that the data used to build the exponential smoothing models is slightly different from that used to build the ARIMA models, because of the problems in obtaining enough data. Since ARIMA models were built for only seven of the twelve items, this section on analysis of seasonality examined the demand data used in building exponential smoothing models, so that all twelve items' demands could be evaluated. The exponential smoothing demand data are plotted in Figure 10 through Figure 21.

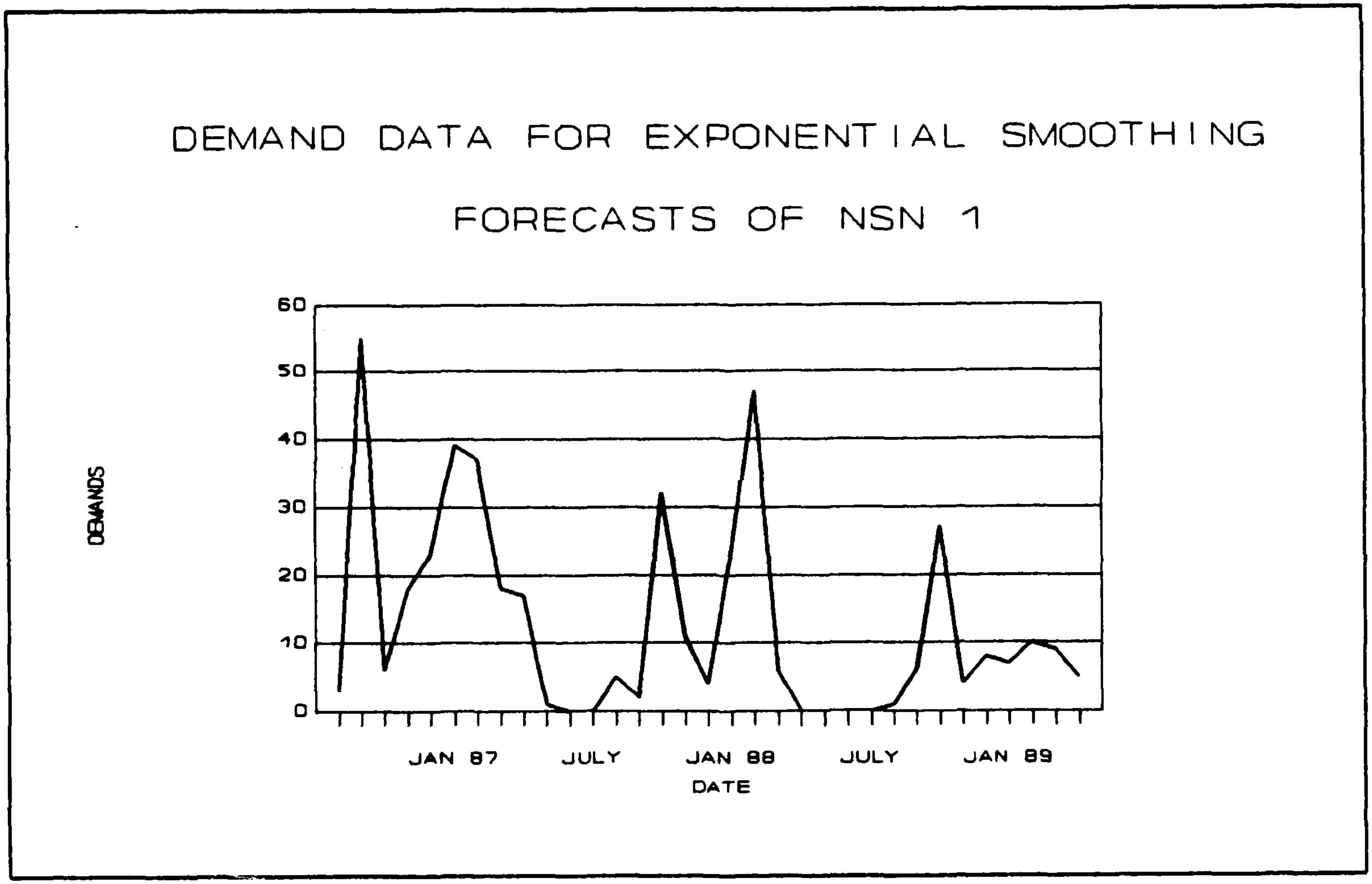

Figure 10. Exponential Smoothing Forecast Demand Data for NSN 1

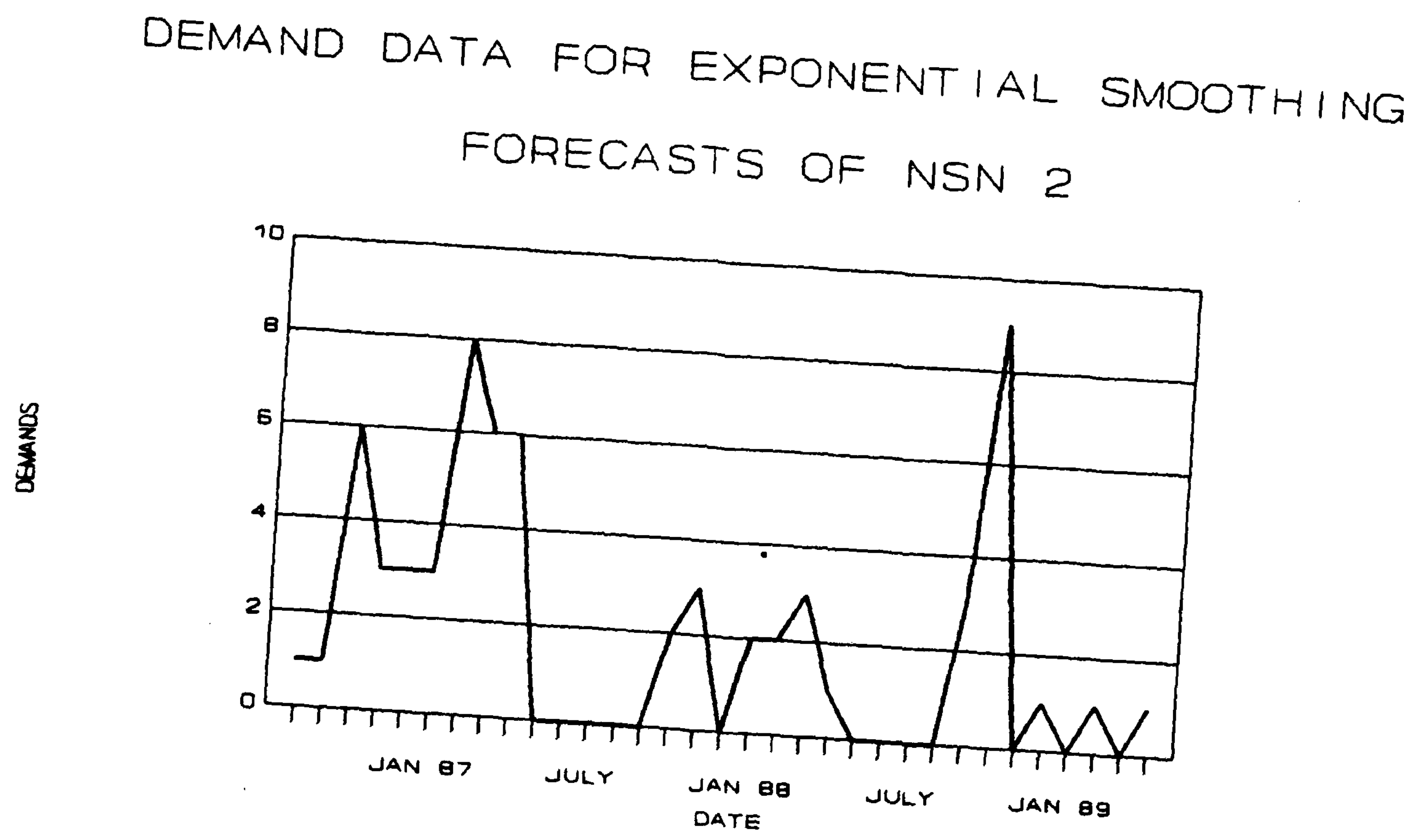

Figure 11. Exponential Smoothing Forecast Demand Data for NSN 2

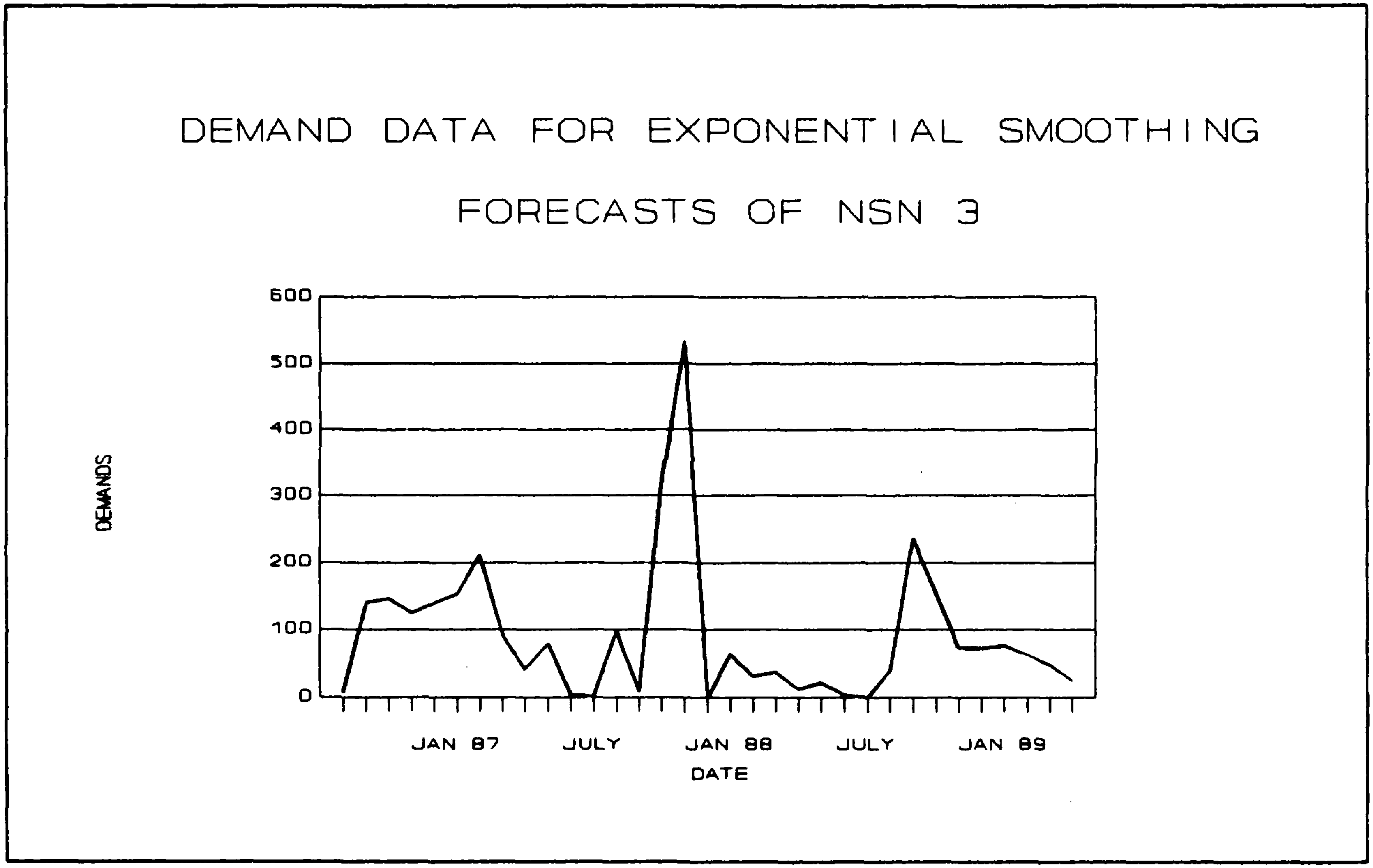

Figure 12. Exponential Smoothing Forecast Demand Data for NSN 3

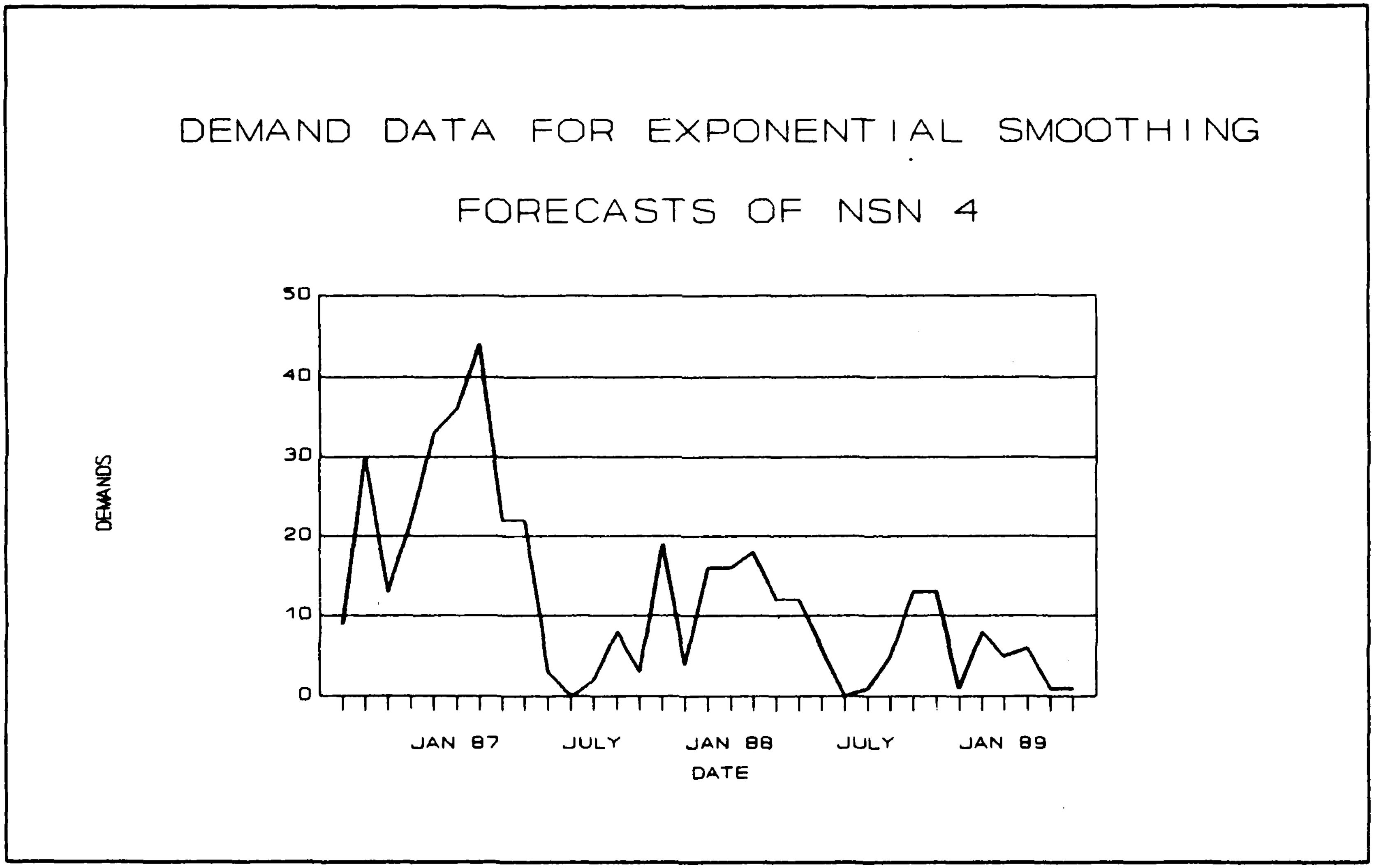

Figure 13. Exponential Smoothing Forecast Demand Data for NSN 4

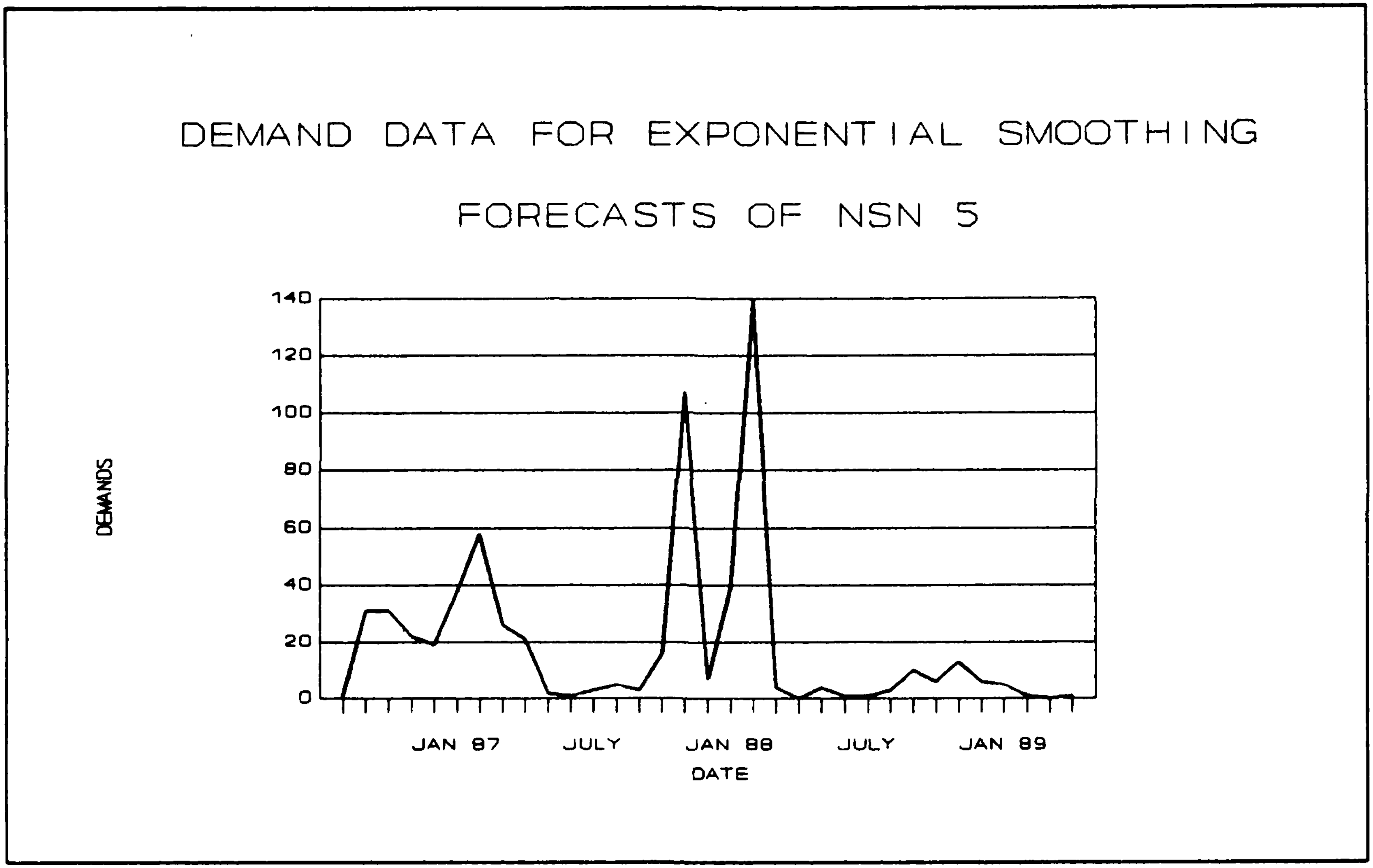

Figure 14. Exponential Smoothing Forecast Demand Data for NSN 5

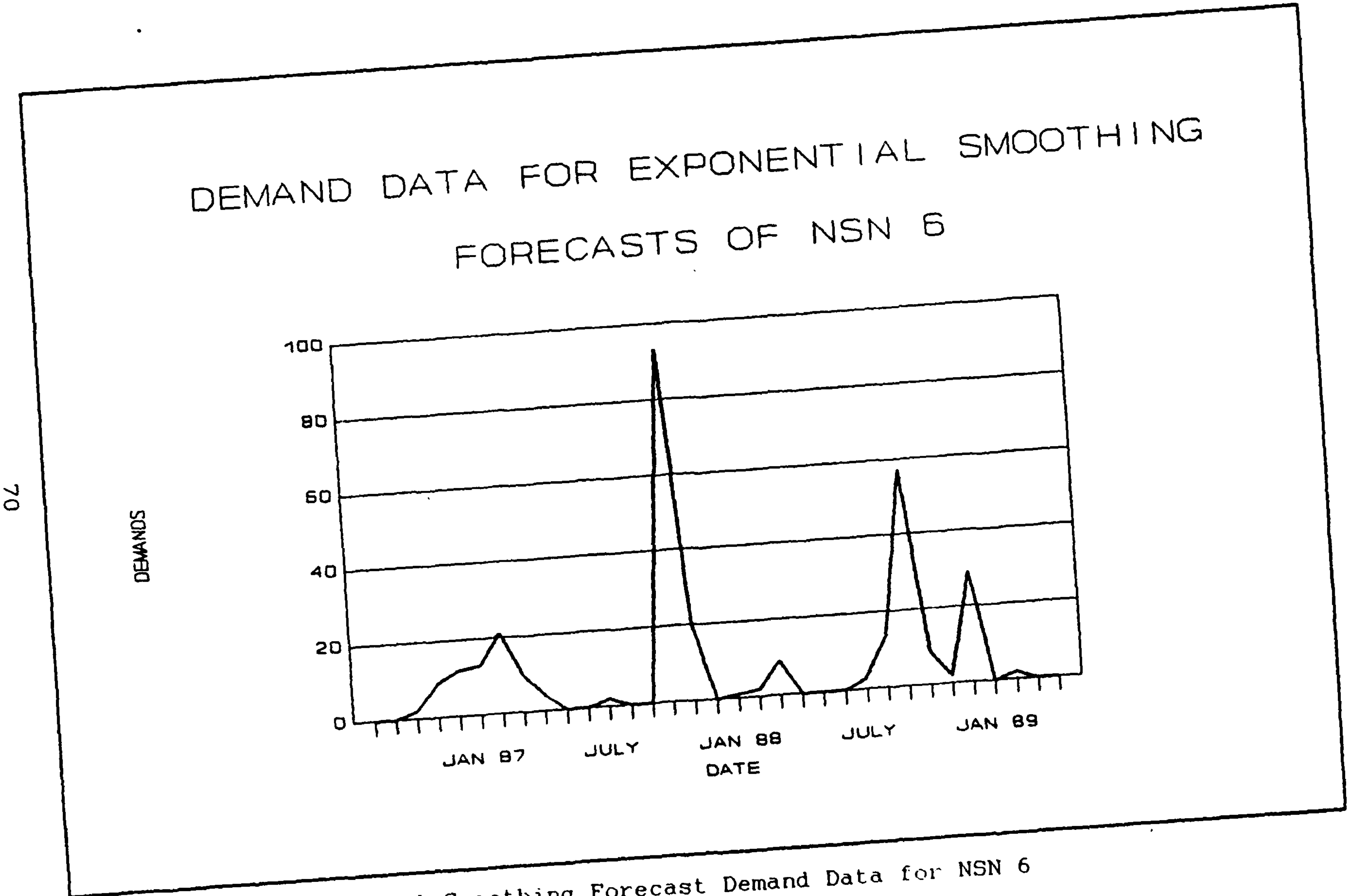

Figure 15. Exponential Smoothing Forecast Demand Data for NSN 6

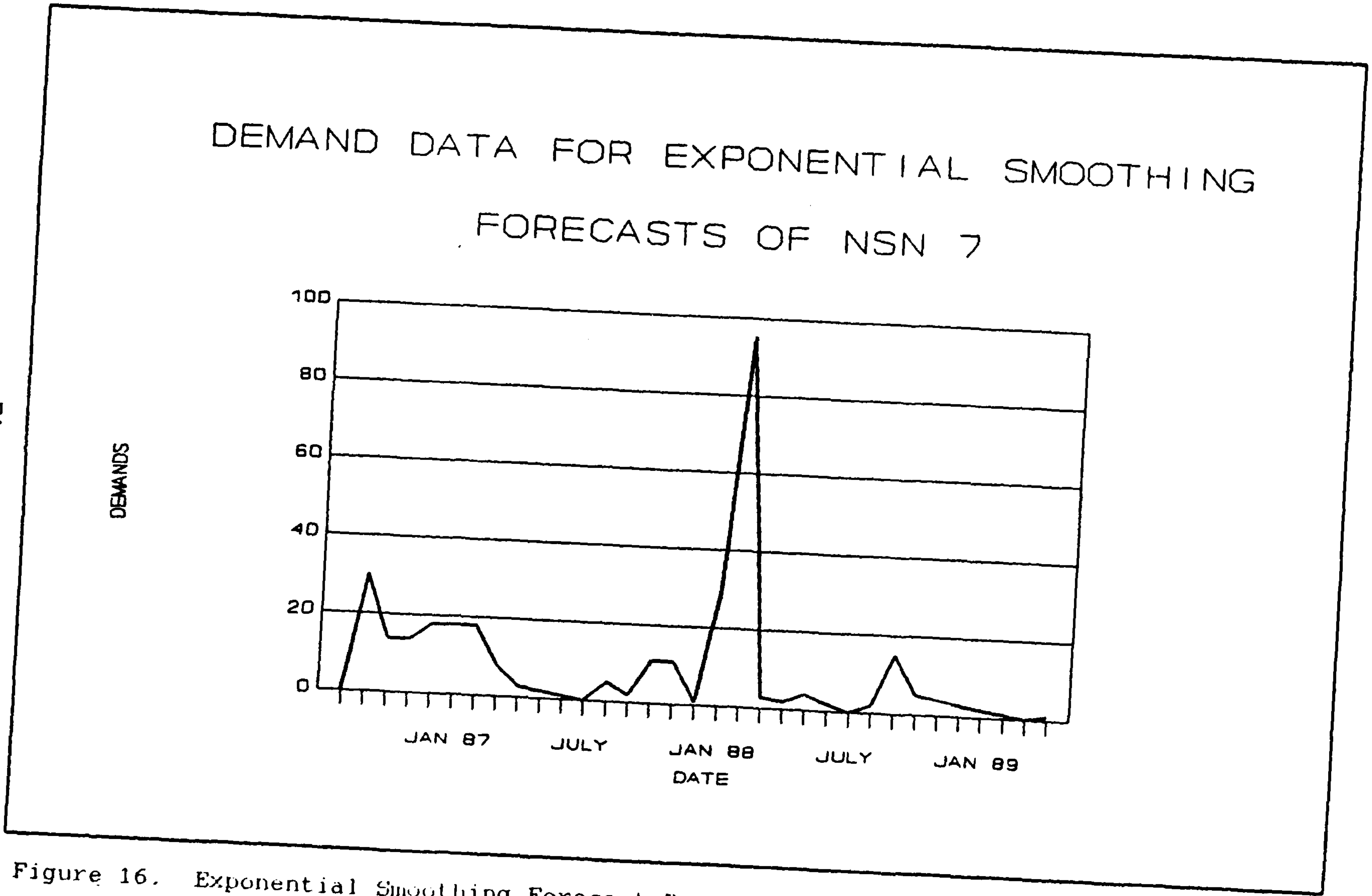

Figure 16. Exponential Smoothing Forecast Demand Data for NSN 7

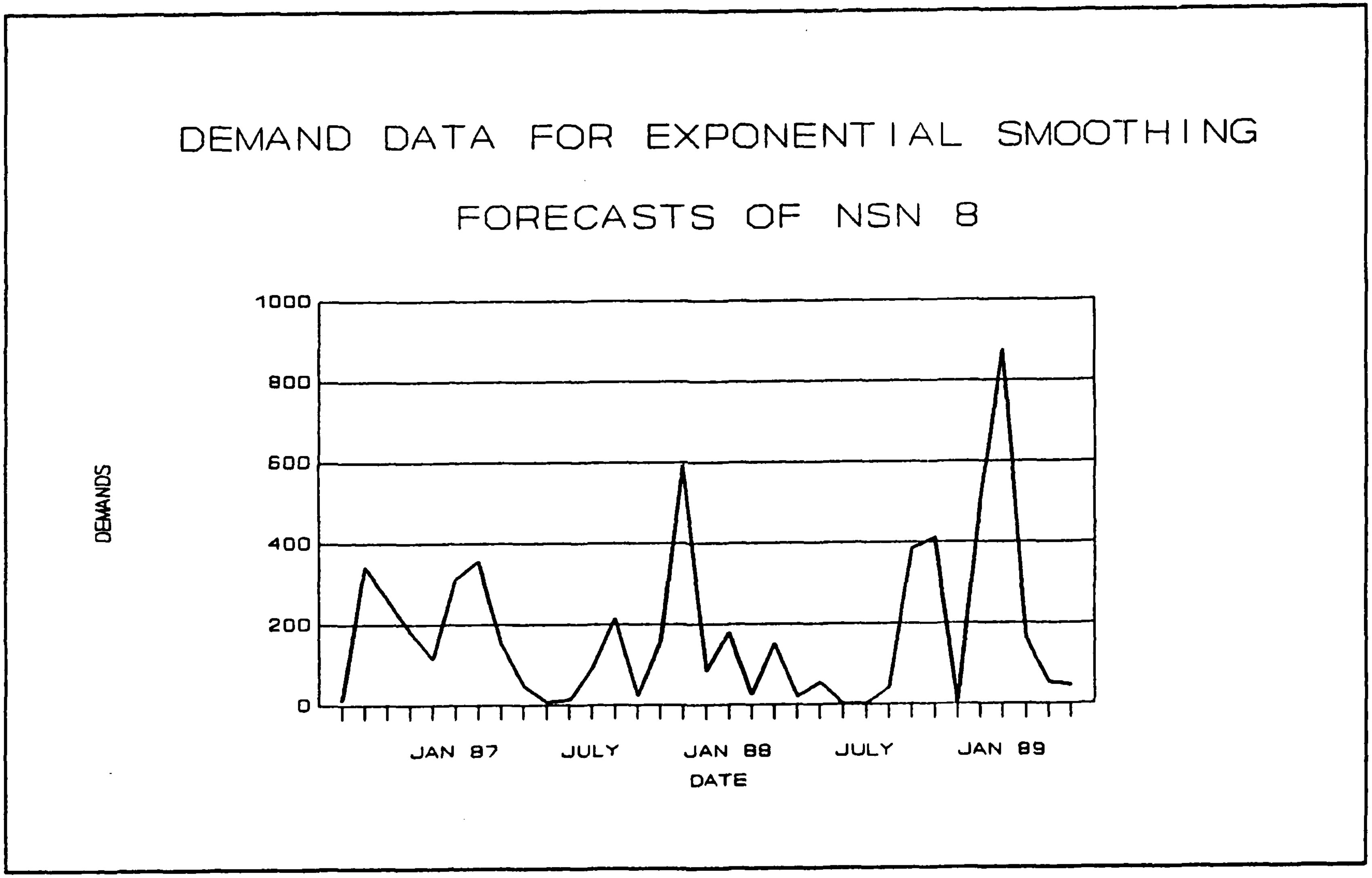

Figure 17. Exponential Smoothing Forecast Demand Data for NSN 8

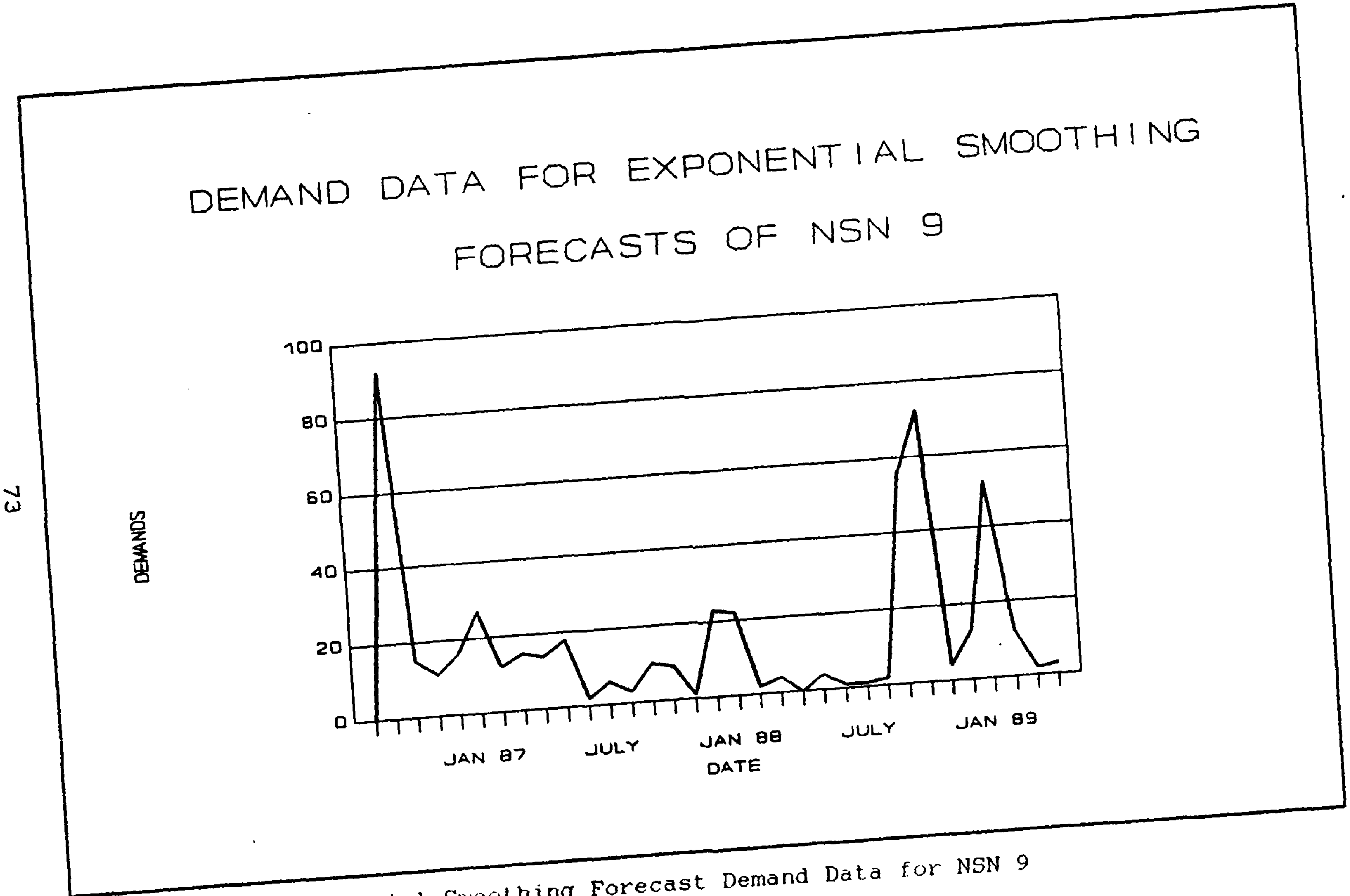

Figure 18. Exponential Smoothing Forecast Demand Data for NSN 9

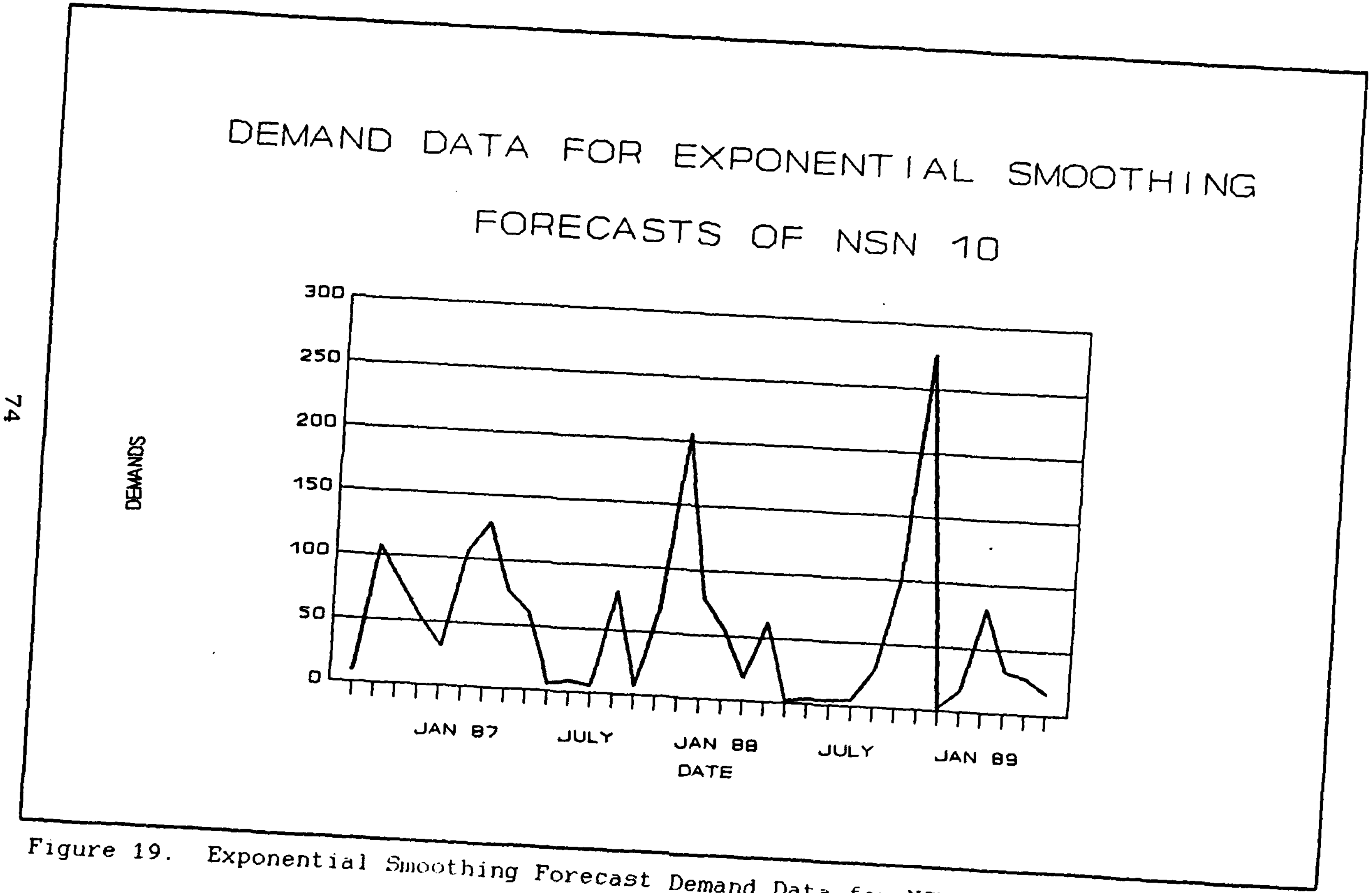

Figure 19. Exponential Smoothing Forecast Demand Data for NSN 10

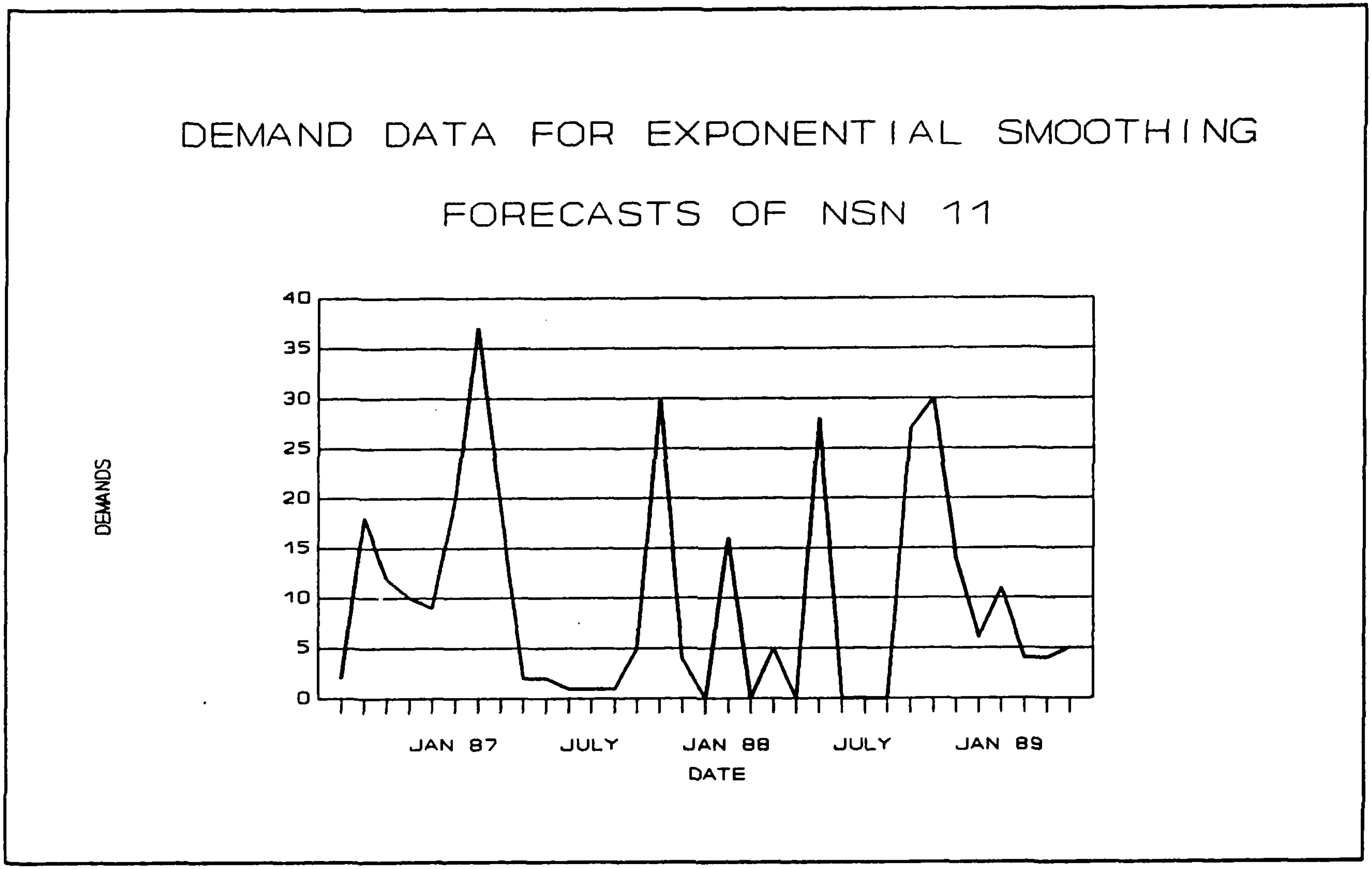

Figure 20. Exponential Smoothing Forecast Demand Data for NSN 11

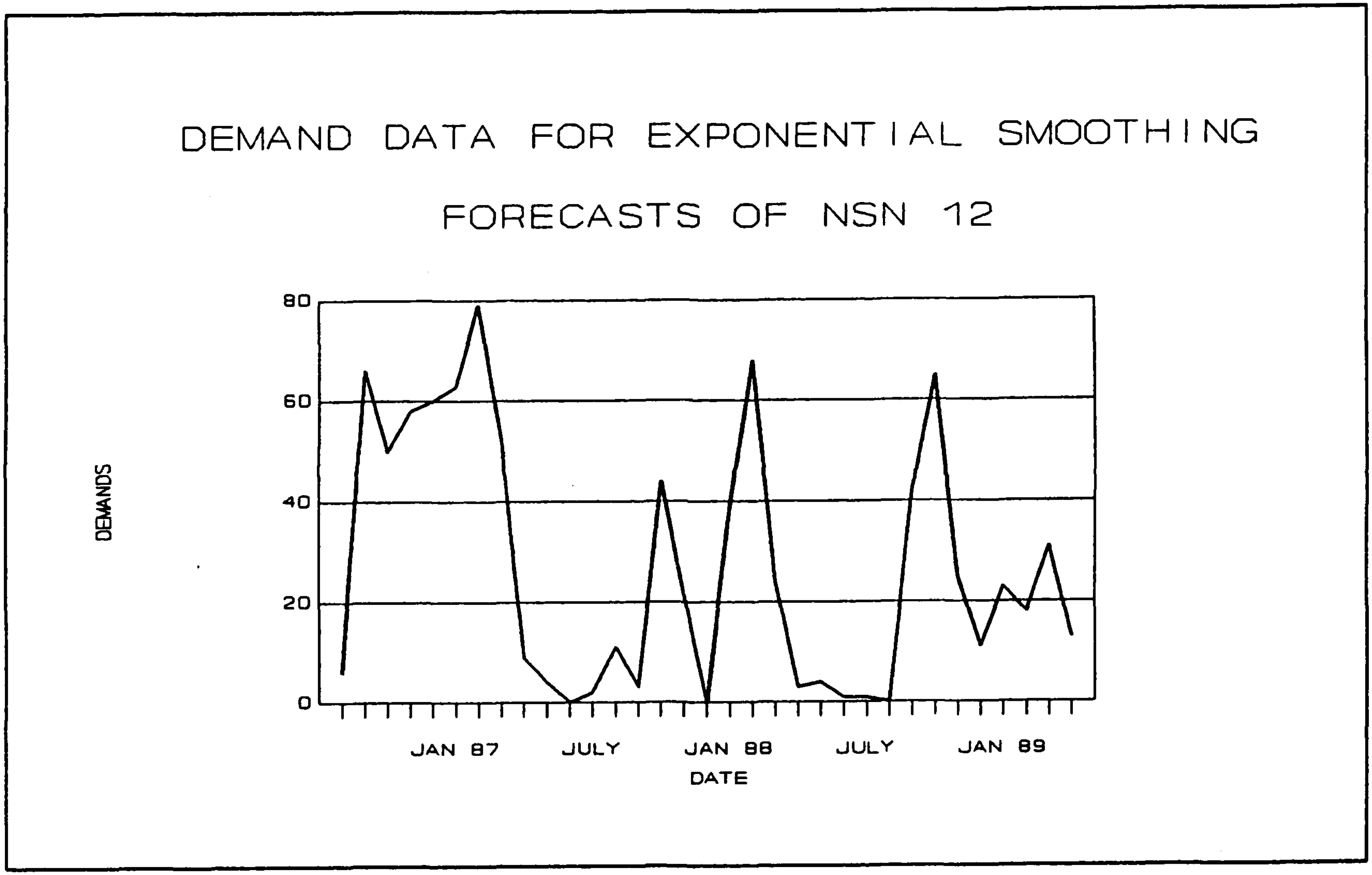

Figure 21. Exponential Smoothing Forecast Demand Data for NSN 12

Attachment 5 lists the data used to create the plots. For the sake of completeness, the demand data used in the Box-Jenkins methodology to generate the ARIMA models are listed in Attachment 6 with the associated graphs in Attachment 7.

Examination of the demands used to build the exponential smoothing models reveals some consistency in which months had the highest demands. Table IV summarizes which months had the high demands for each item. The months of September, October and February had the largest number of high demands. February 1987 had the most high item demands: NSN's 4, 11, and 12 had their highest demands in that month. Three months had the highest demands for two items: September 1986 had more demands than the other months for NSNs 1 and 9; February 1988 had more demands than the other months for NSNs 5 and 7; October 1988 had more demands than the other months for NSN's 2 and 10. Three other months had the highest demands for the final three items: demand for NSN 6 peaked in October 1987, demand for NSN 3 peaked in November 1987, and demand for NSN 8 peaked in January 1989. (Discounting that value as a holdout value would move the peak demand for NSN 8 to November 1987.) In short, the fall and winter months experienced a much greater demand for these items.

The following discussion examines the demand patterns of each NSN. As was noted in Chapter III, plotted seasonal data has similar shaped demand curves from year to year and is consistent in increasing and decreasing from year to

Table IV. NSN Versus Period of Highest Demands

NSN	NOMENCLATURE	PERIOD OF PEAK DEMANDS HIGHEST	2ND HIGHEST
NSN1	BOOT. MUKLUK LARGE	SEP 86	FEB 88
NSN2	PARKA.ECW GRN X-SMA	OCT 88	FEB 87
NSN3	SOCKS.MENS C/W NA10	NOV 87	OCT 87
NSN4	COAT MANS SML-SHOR	FEB 87	JAN 87
NSN5	COAT MAN MED SHT	FEB 87	NOV 87
NSN6	SOCKS.MENS C/W NA14	OCT 87	SEP 88
NSN7	COAT MAN MED LG 33	FEB 88	JAN 88 SEP 86
NSN8	UNDERSHIRT EX WEA L	JAN 89	NOV 87
NSN9	GLOVE SHELLS. CW SZ2	SEP 86	OCT 88
NSN10	SOCKS.MEN.CW.NAUTR9	OCT 88	NOV 87
NSN11	BOOT MUKLUK MANS SM	FEB 87	OCT 87 OCT 88
NSN12	BOOT MUKLUK MED	FEB 87	FEB 88

year. An overlay of a plot of data from one year to the next would show little or consistent change.

NSN 1 had its peak demand of 55 in September 1986. followed by the second highest demand of 47 in February 1988. The next highest demands of 39 and 37 were in January and February 1987. respectively. followed by the 5th highest demand of 32 in October 1987. This pattern of dual peak demands continued in 1988 and 1989 with the highest demands (only 27 and 10. respectively) again in September and February. The lowest demands of 0 were in June and July of both 1987 and 1988. and March and April of 1988. However. in 1987 over 30 items were demanded in March and April. Thus NSN 1 had a fairly well-established pattern of dual peak demands with few demands in June and July.

NSN 2 has a similar demand pattern. but with a smaller number of demands. with the peak demand of 9 in October

1988, followed by the 2nd highest monthly demand of 8 in February 1987. During the three months of October 1987, and March and April 1988, the monthly demands were 6. As with NSN 1, however there were relative peak demands of 3 in November 1987 and March 1988, followed by an October 1988 peak. With such low peak demands, no real pattern of low demands could be found. So, the pattern of dual peaks, several months apart, is also evident in NSN 2's demands.

NSN 3 has a more variable demand pattern. The highest demand of 533 occurred in November 1987, with the second highest demand of 325 occurring in October 1987. The third and fifth highest demands of 236 and 154, respectively, also occurred in consecutive months: September and October of 1988. To continue the pattern, the fourth and sixth highest demands were also in consecutive months, with 211 demanded in February 1987, and 153 demanded in January. The variation in pattern primarily occurred in late 1986, with relatively high demands for four consecutive months. This plateau in demand is unmatched in other years. Low demands, those in the single digits, were consistently in the months of June and July. In all three years, then, demands were high in October and November, but in 1986 and early 1987, the peak demands for the year were spread out and the highest peak demands delayed.

For NSN 4, the demands followed decreasing pattern over the years. The winter (defined as the period of peak demands occurring roughly from September of one year through

March of the following year) of 1986 and 1987 had over 55% of the demands for the period. All of the highest demands for the item occurred between September 1986 and April 1987, with the highest demand of 44 in February 1987. The next two highest demands were for 36 items in January 1987, and 33 items in December 1986. September 1986 had the next highest demand at 30, while November 1986, and March and April 1987 had 22 demands each. This block of higher demands was somewhat repeated a year later with the high demand for the year of 18 again occurring in February 1988. For the winter of 1988-1989, however, the pattern was not repeated. The peak demands of 13 occurred in September and October, and demands declined fairly steadily after that point. Again, low demands were very consistent, occurring in the months of May, June, and July, although November 1988, and March and April 1989 also had demands of only 1. Thus, for NSN 4, declining demands followed a pattern of plateauing for the winter months for two of the three years.

NSN 5's demands follow somewhat a combination of the pattern of NSNs 1 and 2. The peak demand of 139 occurred in February 1988, with the second highest peak demand of 107 in November 1987. Much lower demands of 58 in February 1987 and 38 in January 1987 are the third and fourth highest demands of the previous winter period. The fifth highest demand of 31 occurred in both September and October 1986. Low demands for NSN 5 were somewhat consistent. They occurred from May through September in 1987 and March through

August in 1988, although other months, such as February and April 1989 also had low demands. So, again, there is a pattern of high demands in the fall, a drop in demands through December and January, followed by a high demand in February as in NSNs 1 and 2's demands. This pattern ends in the final winter of demand data with two relative peak demands of 10 and 13 in September and November 1988 respectively, but with no follow-on peak demand in February. As in the case of NSNs 1 and 4, the demands almost established a pattern for the first two years which changed for the winter of 1988-1989.

NSN 6 followed even less of a pattern. The peak demand of 93 was in October 1987, while the second highest demand of 57 was in September 1988. The third highest demand of 29 occurred in December 1988, while the fourth highest demand of 21 was in February 1987. The fifth highest demand was 20 in November 1987. In the winter of 1986-1987 the peak demand was in February. The following winter (1987-1988) the peak demands were in consecutive months, October and November. The final winter the peak demands were split into the two months of September and December. The low demands are also inconsistent. In 1987, they extend from April through September, while in 1988 they extend from December (1987) through July. So there is a less clear pattern to the demands of NSN 6.

NSN 7 also failed to show a clear demand pattern. The peak demand of 90 occurred in February 1988. The second highest demands of 30 occurred during January 1988 and September 1986. The fourth highest demands of 18 occurred in December 1986, and January and February 1987. The next highest demand (seventh) occurred in September 1988. A mixed, weak, pattern might be gleaned from these demand data if the highest peak of over 90 were not so high. Peak demands occurred twice in September, and twice in January and February. The low demands are relatively consistent, running from March through September in 1987 and March through August in 1988. In conclusion, there is not much of a visual pattern to the NSN 7 demands.

NSN 8 had by far the highest demand rate of any of the NSN's studied, but little pattern. The monthly demands ranged from 2 to 873, the highest demand occurring in January 1989. The second highest demand of 590 fell in November 1987, while the third highest demand of 502 occurred in December 1989. October 1988 had the fourth highest demand of 412 and February 1987 had the fifth highest demand of 357. The lowest monthly demands were fairly consistent, occurring in May and June of 1987 and June and July of 1988. Other than this, no obvious pattern reveals itself in the data. The winter 1986-1987 demand data consists of a number of relatively high demands from September to March, the two highest occurring in September and February. The following winter's demand data is characterized by a large peak in November amidst a saw-tooth pattern with relatively large demands in August, October, January, and March. The winter of 1988 and 1989 is still different with two large peaks, one centered around October, the other centered around January. So, in no two years are the peak demands in the same months, nor are the patterns of demand similar in any of the three winters.

For NSN 9, the demand pattern is more apparent. The peak demand of 92 occurred in September 1986. The second highest demand of 72 occurred in October 1988, while the third highest demand of 56 occurred in September of the same year. The fourth highest demand of 52 followed in January 1989, while the fifth highest demand of 27 took place in January 1987. The lowest demands were not consistent. In 1987 the lowest demands occurred only in June, July, and August (and November), while in 1988 February through August had low demands. Smaller, but relatively high demands also occurred in December of 1987 and January of 1988 along with smaller yet relatively high demands in September and October of 1987. The pattern is fairly evident although not consistent in magnitude, since the winter 1987-1988 peaks are so low. For NSN 9, the high demands occur in January fairly consistently, with another peak in demands in September or October or both September and October.

The NSN 10 demand pattern is similar to that of NSN 9. The highest demand of 277 occurred during October 1988, while the second highest demand of 206 occurred in November 1987. The third, fourth and fifth highest demands of 129, 107 and 105 respectively occurred in February 1987.

September 1986, and January 1987. The lowest demands occurred in May through September 1987 (with the exception of a higher August value), while occurring from only April through July of 1988. The high demands were more consistent, occurring in October and November, and to a lesser extent in January or February. Each winter period, especially 1986-1987 and 1988-1989, had at least a double peak demand. The winter 1987-1988 demands showed a pattern of one central peak demand in November, a lesser one in August and another lesser one in March.

The demand data for NSN 11 has a less clear-cut pattern. The highest demand of 37 took place in February 1987. The next highest demand of 30 occurred in both October 1987 and October 1988. The fourth highest demand of 28 occurred in May 1988, while the fifth highest demand of 27 occurred in September 1988. The low demands for 1987 took place April through September, but in the following year occurred during February through August, with the previously mentioned exception of May 1988. The winter 1986-1987 demand data have dual peaks, one in September, the other in February. The next winter, dual peak demands occurred, one in October, the second in January. These were followed by an unusual peak in May of 1988, which was subsequently followed by still two more peaks in September and October and a minor one in January 1989. Excepting the May peak, September, October, and January tended to have peak demands, but there is no apparent consistency to their relative heights because of the changes in which months had the greatest demands from year to year.

NSN 12 has a similar demand pattern. The highest monthly demand of 79 took place in February 1987. The next highest demand of 68 occurred in February 1988, followed by the third highest demand of 66 in September 1986. The fourth highest demand of 65 occurred in October 1988 and the fifth highest demand of 63 occurred in January 1987. The low demands occurred April through September in 1987 (with August an exception) and in April through August in 1988. Again the pattern of dual peaks occurring inconsistently throughout the year is evident. One peak occurs in September or October followed by another in January or February, but there is no consistency to the relative heights of the peaks for given months from year to year.

General Demand Patterns. The most striking aspect of the plots are the peaks which generally occur in the fall and winter months, followed by low demands in the spring and summer months. A pattern, although sometimes slight, exists in the demands of NSNs 1, 2, 3, 5, 9, 10, 11, and 12. (Note that these are the same NSNs, with the addition of NSN 2, that showed enough of a consistent pattern to "pass" the Wilcoxon Signed Rank Test.) The pattern consists of high demand characterized by a peak during one or more of the months September through November, followed by low demands in December and another peak in January, February, or March. NSN 4's demands had a pattern of plateaus instead of peaks during the months December through February. The other NSNs. 6. 7. and 8 had little or no obvious pattern.

Several possible reasons exist for the demand data differing from year to year. First. organizations tend to buy cold weather gear in large quantities only a few times a year. so year to year changes in when large organizations bought winter gear could easily change monthly demands from year to year. Second. the supply personnel could change the month of peak demands from year to the next by changing when they ask organizations to request winter gear. and by ordering differing quantities according to what the response is. A third possibility is that changing budgets could cause changes in how the organizations choose the spend their money. Years with low demands across the spectrum of cold weather gear could mean restrictions on who was authorized to possess an item and how many of a given item an organization could procure. or a large decrease in the manning of the organization. A different possibility is that mild weather one year could affect demands both that year and the next. Fewer items will be used during a mild winter and those that are used will be used less frequently so replacements would be fewer the following year. Another possible cause for changing demand is replacement of the item by another. either because it falls out of favor. or because it is simply replaced by another NSN. This. however. is unlikely for the items considered here. Still another possibility is that the extremely low demand rates of some items just do not provide sufficient data to make an underlying demand pattern visible.

Grouped Item Demand Evaluation. In addition to the individual items, three different sets of grouped, like, items were evaluated. Three sizes each of mukluks, cold weather socks, and coats were among the items selected for analysis.

The mukluk demands, cold weather sock demands, and coat demands are presented in Figure 23, Figure 24, and Figure 22, respectively. An examination of the demand patterns for like items showed some similarities and some differences. The mukluks (NSNs 1, 11, and 12) were represented by the same basic demand pattern of two or three peaks of varying height over each winter's heavy demand period.

The socks' (NSNs 3, 6, and 10) demand patterns were more similar over the three winter period. The first winter had a plateau shaped demand pattern followed by a single large peak the next winter, and finally a single peak the third winter followed by relatively level demands or a single additional peak. The coats' (NSNs 4, 5, and 7) demand patterns were less similar. NSNs 5 and 7 had basically the same demand pattern with plateaus and peak switched during the first winter, and two peaks in the second winter's demand of NSN 5 versus only one for NSN 7. However, NSN 4 followed an slightly different demand pattern with no peak demand during the second winter. So, for each

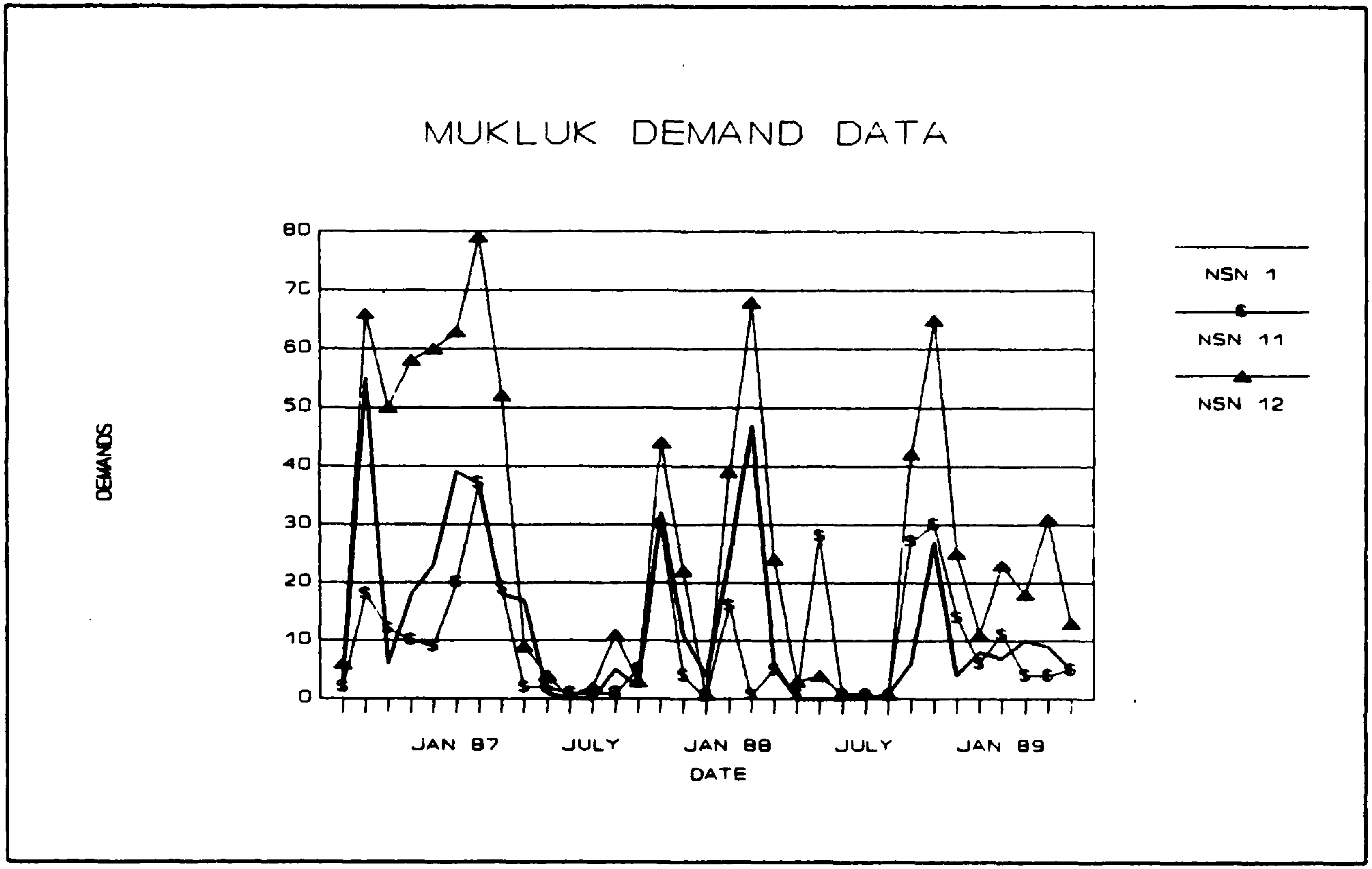

Figure 22. Mukluk Demand Data

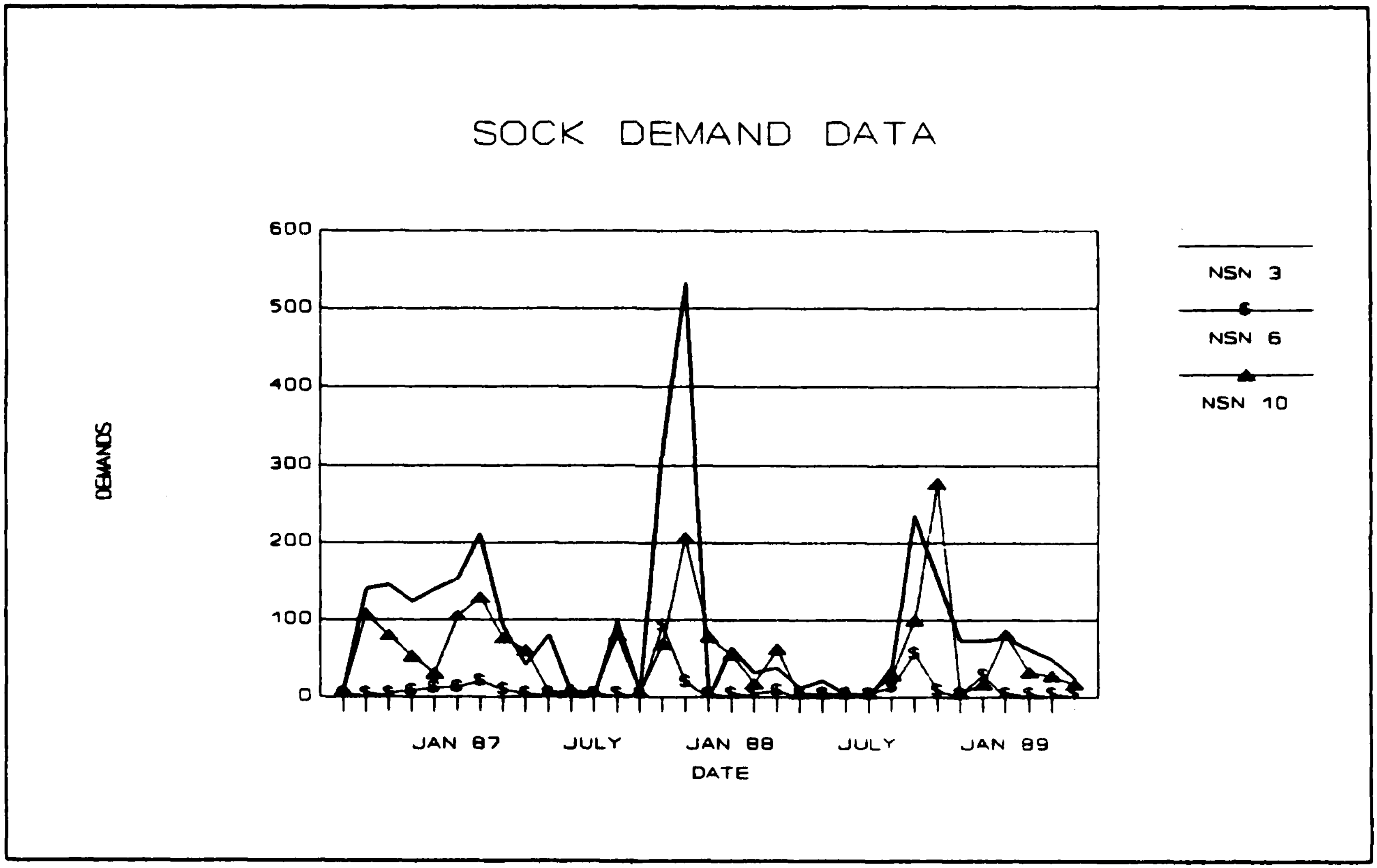

Figure 23. Sock Demand Data

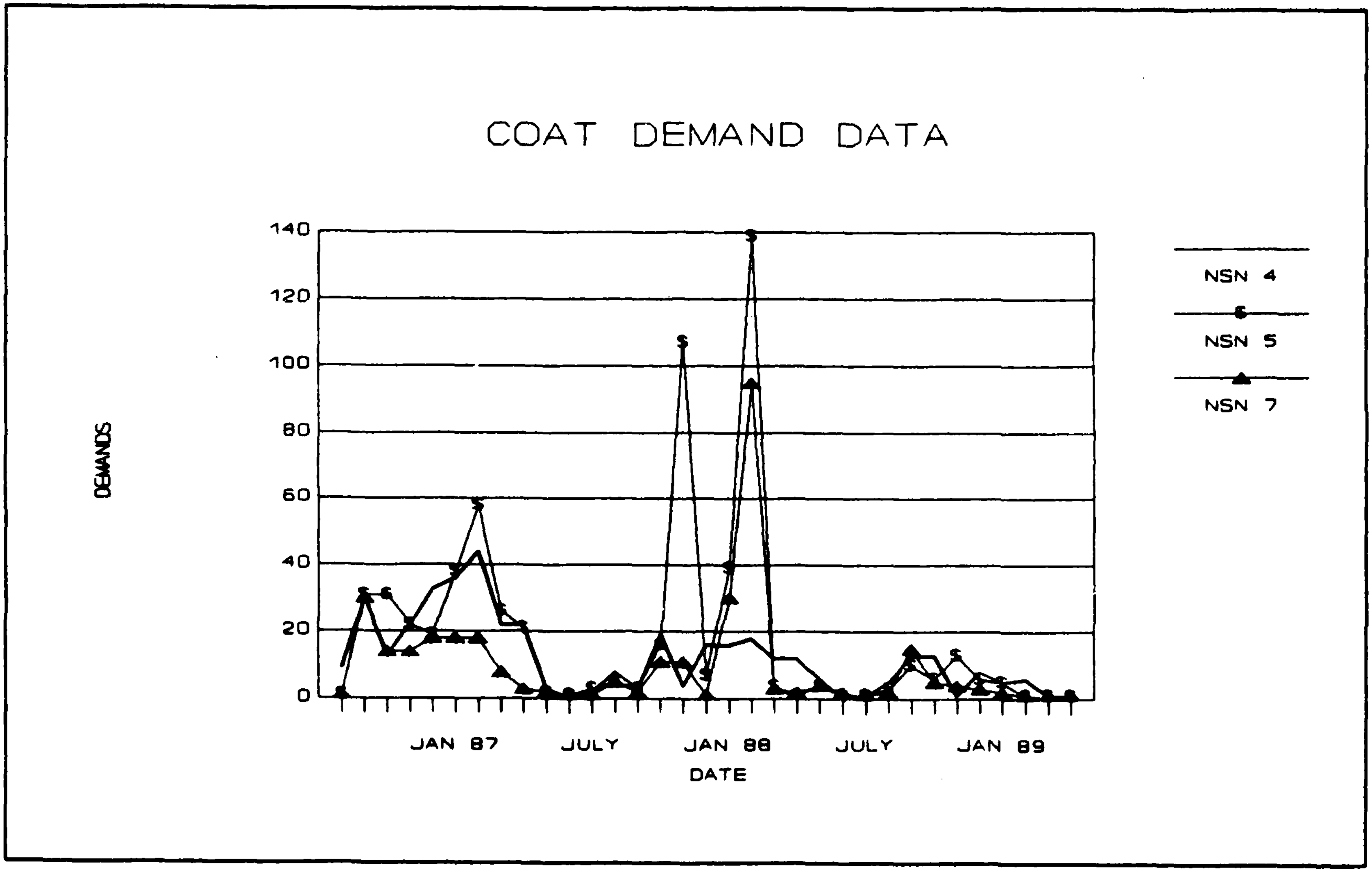

Figure 24. Coat Demand Data

of the three groups, although some similarities could be found in the demand patterns of like items, the similarities were limited.

<u>Autocorrelation Function Evaluation</u>. The limited similarities in the demand patterns of like items are also evident in the ACFs of the items' demand data shown in Attachment 7. As an example, the ACF of NSN 1 is displayed in Figure 25. The calculated ACFs are presented in a bar format, while the upper and lower bounds of significance for the ACFs at each lag are presented as lines. These significance bounds are set according to the rule that for the first three lags an autocorrelation greater than one-half the standard error is significant, for the next three lags an autocorrelation greater than the standard error is significant, for lags 7-12 an autocorrelation greater than twice the standard error is significant, and for higher numbered lags an autocorrelation greater than three times the standard error is significant (7).

None of the NSNs had a strong enough seasonal demand pattern to generate a statistically significant seasonal ACF, although some were close to being significant. For example, NSNs 5 and 8 had relatively strong autocorrelations at lag 12, but in both cases they were not statistically significant. Interestingly, NSNs 10 and 12 had high autocorrelations at the 11th lag. This implies a demand pattern shifting from one month to the next each year. Finally, NSN 2 had a demand pattern with a relatively

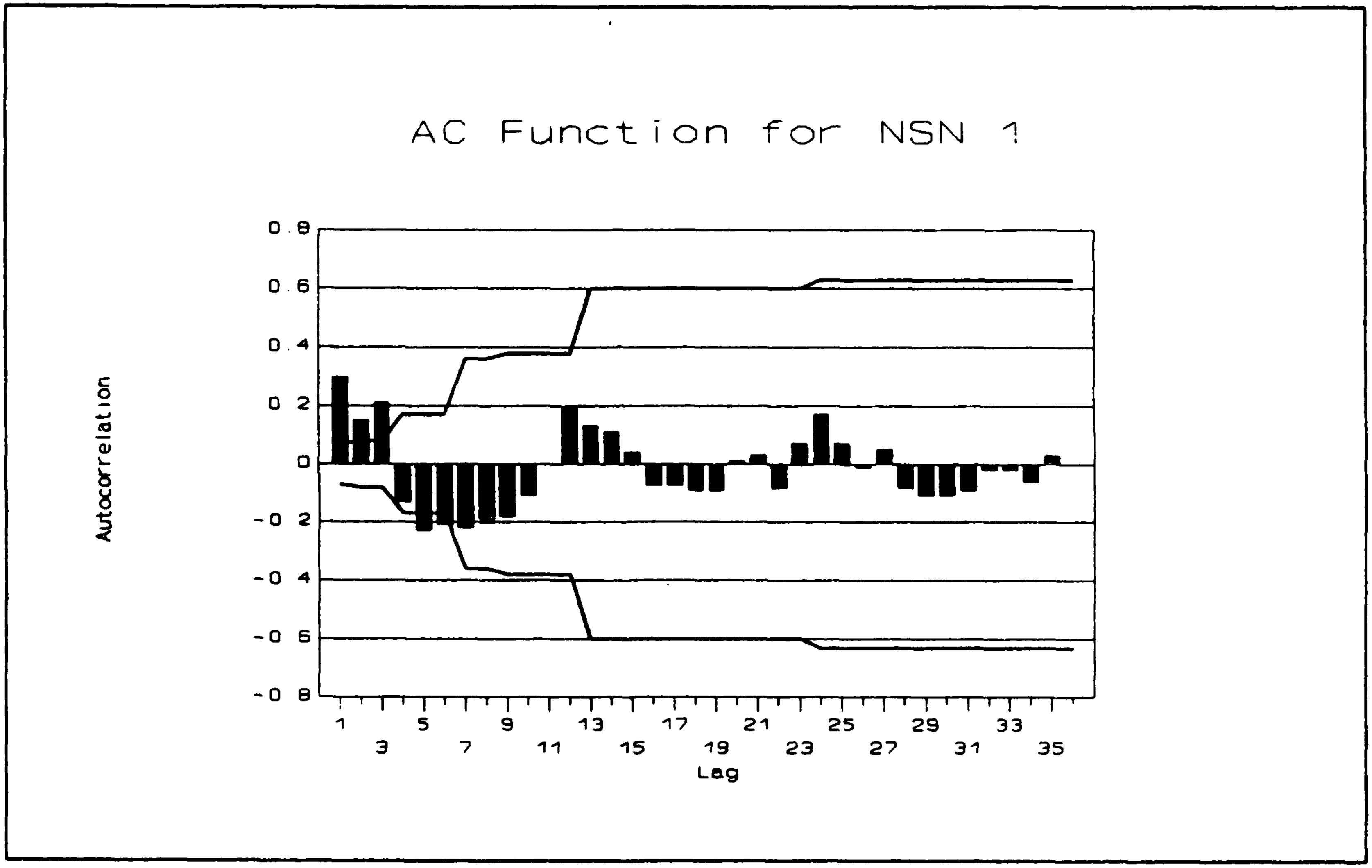

Figure 25. Autocorrelation Function for NSN 1

significant 5th and 6th lag, leading to the conclusion that demands were on a six month cycle instead of the expected 12 month cycle.

The net results of the seasonal tests were that the demand data are not strongly seasonal. Although the demand data appeared superficially seasonal, closer analysis showed the demand data generally do have some seasonal patterns, although they are not very strong. The evaluation of the ACFs gave similar results. None of the demand data had a strong seasonal pattern. Having examined the seasonality of the items, the performance of the forecast models will be discussed next.

Exponential Smoothing Models

Two types of exponential smoothing models had their forecasting abilities tested. The first was simple exponential smoothing [14]. The second was Winters' seasonal exponential smoothing [21], [22], [23], and [24]. For each item a value for the parameters (α for simple exponential smoothing: and α, β, and Γ for seasonal smoothing) were generated. These values are listed in Table V.

A further analysis was performed on the three groups of like items to determine if any relationships could be found between the exponential smoothing models for each item in each group. To determine if the parameters for the exponential smoothing models were the same for the different sizes within each group a one sample t-test was performed on the

Table V. Exponential Smoothing Parameters

	EXPONENTIAL SMOOTHING PARAMETERS			
	SINGLE	WINTERS'		
NSN	α	α	β	Γ
1	.028	.050	.046	.332
2	.044	.228	.028	.410
3	.018	.030	.030	.244
4	.684	.073	.061	.391
5	.038	.038	.000	.251
6	.054	.040	.055	.075
7	.035	.035	.026	.277
8	.076	.061	.050	.229
9	.004	.000	.033	.266
10	.044	.027	.003	.163
11	.031	.012	.013	.271
12	.848	.062	.020	.367

simple exponential smoothing parameter, while a one way analysis of variance (AOV) was performed on the three parameter values for the seasonal model. The results of those tests are in Table VI.

For the mukluks the 1.14 t-test value for the simple exponential smoothing models indicates that the three simple exponential smoothing models are not statistically different. The large F value of 75.55, however, leads to the conclusion that the Winters' seasonal exponential smoothing models for the three mukluk sizes are indeed different.

For the socks, (NSNs 3, 6, and 10), the results are different. The simple exponential smoothing models are statistically different at the 95% confidence level. The Winters' seasonal exponential smoothing models, however, are statistically different at a 95% confidence level.

Table VI. T-test and AOV Results for Exponential Smoothing Models

GROUP	NSNs	EXPONENTIAL SMOOTHING SIMPLE	WINTERS'
		T-VALUE	F-VALUE
MUKLUKS	1.11.12	1.14	75.55
SOCKS	3.6.10	3.60	6.43
COATS	4,5,7	1.17	31.11

In the case of the coats, their simple exponential models are not statistically different at a 95% confidence level. However, one could be confident in saying the three items could not be represented by a single Winters' seasonal exponential smoothing model at the 95% confidence level.

Given the above information, then, a base could choose to use a single simple exponential smoothing model to forecast demands for mukluks, another model for coats, but would need three models for socks. Since the sample is so small, one cannot tell if this would hold true for all groups of similar but different sized items. It must be noted that the accuracy of these models has not yet been evaluated.

In the case of Winters' seasonal exponential smoothing, one model could not be considered appropriate for the different sizes of mukluks, socks, and coats. It is reasonable that one Winters' seasonal exponential smoothing model is less likely to work for more than one item since there are three parameters to match, not just one.

The net result of the exponential model analysis is that, based on the limited sample used, one simple exponential smoothing model may be used, in some cases, to forecast different sizes of similar items, but not one Winters' seasonal exponential smoothing model. For each NSN a separate Winters' seasonal exponential smoothing model was required. One possible reason is that with the difference in demand patterns between similar items identified earlier, the more sensitive Winters' models followed demands for each item so closely they could not reasonably model other items' demands.

Next, ARIMA models will be considered to observe how they model the demands for seven of the sample items. Each ARIMA model will be compared with the forecasts generated by the simple and Winters' seasonal exponential smoothing models.

ARIMA Models

Only seven items were forecast using ARIMA models because of the break in the data for the period 1984 through the end of 1986. Table VII contains a summary of the models obtained through the Box-Jenkins methodology, while Attachment 8 lists the diagnostic outputs from the computer. Recall, AR and MA stand for autoregressive and moving average respectively, while RDIF stands for regular differenced. No twelve period seasonal parameters were necessary to model the data, nor was any seasonal differencing necessary, with

Table VII. Box-Jenkins Methodology Models

	PARAMETER TYPE	AND VALUE
NSN 1 (A)	AR 1	-0.53133
	AR 2	-0.36419
	RDIF	1
NSN 2	N/A	
NSN 3 (B)	MA 1	-0.28883
	MEAN	104.38
NSN 4 (C)	N/A	
NSN 5 (C)	AR 3	0.62381
	AR 6	-0.47797
	MA 1	0.42724
	MA 2	0.26339
	RDIF	1
NSN 6 (B)	N/A	
NSN 7 (C)	N/A	
NSN 8	N/A	
NSN 9	AR 1	0.38984
	AR 3	0.26171
	MA 2	0.24589
	MEAN	20.036
NSN 10 (B)	MA 1	0.65234
	MA 2	0.41991
	RDIF	1
NSN 11 (A)	MA 3	0.27372
	MA 6	0.21114
	MEAN	8.1945
NSN 12 (A)	AR 3	0.16814
	AR 6	-0.34273
	MEAN	26.19

(A) = MUKLUKS (B) = SOCKS (C) = COATS

the exception of a seasonal parameter at lag 6 for NSN 5. This means that the seasonality of the data was less important in modeling the data than other factors. Table VIII lists the models in their mathematical notation.

As in the case of the exponential smoothing models an attempt was made to find similar models between like items This failed. The demand patterns of like items were not similar enough. The models for mukluk demand data include a differenced autoregressive 1 and 2, and two models with terms at 3 and 6 periods, the first in moving averages. the second in autoregressive terms. The sock demand data models are less different in that both include moving average terms. although one has only a single moving average term and is undifferenced and the other has two moving average terms and required differencing. Only one model for coat demand data was generated, so no comparisons between coat models could be made.

Because of the increased complexity of the ARIMA models, the models are less likely (as was seen in the case of exponential smoothing) to be transferable from one item to another in spite of similar demands. The more closely the demand history is fitted by the equations, the less likely that equation will be adequate or even useable on another item. as was seen with the exponential smoothing models.

Table VIII. Mathematical Notation for Box-Jenkins Models

NSN 1

$$(1-\phi_1 B - \phi_2 B^2)(1-B)Y_t = e_t$$

$$Y_t = .469Y_{t-1} - .167\ Y_{t-2} + .364\ Y_{t-3} + e_t$$

NSN 3

$$Y_t = (1-\theta_1 B)e_t + \mu$$

$$Y_t = e_t - .289e_t + 104.38$$

NSN 5

$$[(1-\phi_3 B^3 - \phi_6 B^6)(1-B)]Y_t = e_t(1-\theta_1 B - \theta_2 B_2)$$

$$Y_t = Y_{t-1} - .624Y_{t-3} - .624Y_{t-4} + .478Y_{t-6}$$

$$- .478Y_{t-7} + e_t - .427e_{t-1} + .263e_{t-2}$$

NSN 9

$$[(1-\phi_1 B - \phi_3 B^3)]Y_t = e_t(1-\theta_2 B_2) + \mu$$

$$Y_t = .390Y_{t-1} + .261Y_{t-3} + e_t + .246e_{t-2}$$

$$+ 20.04$$

NSN 10

$$(1-B)Y_t = e_t(1-\theta_1 B - \theta_2 B_2)$$

$$Y_t = Y_{t-1} + e_t - .652e_{t-1} - .420e_{t-2}$$

NSN 11

$$Y_t = e_t(1-\theta_3 B^3 - \theta_6 B_6) + \mu$$

$$Y_t = e_t - .274e_{t-3} - .211e_{t-6} + 8.19$$

NSN 12

$$[(1-\phi_3 B^3 - \phi_6 B^6)]Y_t = e_t + \mu$$

$$Y_t = .168Y_{t-3} - .343Y_{t-6} + e_t + \mu$$

Forecasts

The forecasts from the various forecasting techniques are presented in Attachments 9, 10, 11, and 12 for December data, January data, February data and March data respectively. The December data was used to forecast demands for January through April, the January data was used to forecast demands for February through April, and so on. Note that by their very nature, the simple exponential smoothing and SBSS methods make a single forecast which is projected forward for all months. The Winters' and ARIMA models, however, project forward different monthly forecasts due the their explicit consideration of seasonality. Attachment 14 contains graphs of the forecasts plotted against each other and the holdout sample.

Model Analysis

The different models, simple exponential smoothing, Winters' seasonal exponential smoothing, ARIMA, and SBSS, were evaluated, as was mentioned in Chapter III, by how many times each model had the lowest MSE. In other words, for each NSN, the number of times each model outperformed the others for each of the four forecast periods (December, January, February, and March) was determined. The number of times each model had the best (lowest) MSE is recorded in Table IX. The MSE values used to determine the values in Table IX are listed in Table X through Table XIII. Recall that only seven items had demand data which could be used to

Table IX. Number of times each model was "best"

	EXPONENTIAL SMOOTHING			
	SIMPLE	WINTERS'	BOX-JENKINS	SBSS
NSN 1	0	2	1	1
NSN 3	0	4	0	0
NSN 5	0	0	4	0
NSN 9	1	2	0	1
NSN 10	0	4	0	0
NSN 11	0	1	2	1
NSN 12	0	0	2	2
TOTALS	1	13	9	5

make ARIMA models, so NSNs 2, 4, 6, 7, and 8 are not considered in this analysis.

Winters' seasonal exponential smoothing is clearly the best forecast method using this criterion, having the lowest MSE in 13 of 28 forecasts. ARIMA models were the second

Table X. Model MSE's for December Forecast

MSE FOR THE VARIOUS MODELS
DEC FORECAST

	BOX JENKINS	EXPONENTIAL SMOOTHING		SBSS
		WINTERS'	SIMPLE	
NSN 1	23.38	48.93	23.49	22.36
NSN 3	2880.88	195.40	1653.97	3725.54
NSN 5	13.06	840.41	294.39	276.70
NSN 9	270.41	268.89	431.60	430.79
NSN 10	4105.97	480.75	831.73	1108.13
NSN 11	16.23	32.51	22.04	14.13
NSN 12	198.88	173.78	97.04	46.63

Table XI. Model MSE's for January Forecast

MSE FOR THE VARIOUS MODELS
JAN FORECAST

	BOX JENKINS	EXPONENTIAL SMOOTHING WINTERS'	EXPONENTIAL SMOOTHING SIMPLE	SBSS
NSN 1	7.67	29.66	19.88	18.37
NSN 3	3538.07	341.71	2257.15	4224.93
NSN 5	14.04	1248.65	306.24	279.84
NSN 9	367.33	244.06	1527.47	122.38
NSN 10	5339.82	1040.61	1247.37	1411.93
NSN 11	7.58	49.50	38.00	17.36
NSN 12	150.64	234.36	58.46	58.38

Table XII. Model MSE's for February Forecast

MSE FOR THE VARIOUS MODELS
FEB FORECAST

	BOX JENKINS	EXPONENTIAL SMOOTHING WINTERS'	EXPONENTIAL SMOOTHING SIMPLE	SBSS
NSN 1	5.50	4.19	28.80	33.57
NSN 3	4171.21	88.14	2485.59	6045.36
NSN 5	13.68	82.85	276.81	294.94
NSN 9	377.85	46.03	111.34	201.28
NSN 10	5127.95	604.16	1178.10	1897.49
NSN 11	5.66	17.20	22.81	18.87
NSN 12	81.47	87.87	92.90	81.88

Table XIII. Model MSE's for March Forecast

MSE FOR THE VARIOUS MODELS
MAR FORECAST

	BOX JENKINS	EXPONENTIAL SMOOTHING WINTERS'	EXPONENTIAL SMOOTHING SIMPLE	SBSS
NSN 1	11.83	0.86	46.24	10.54
NSN 3	4399.67	60.06	3058.09	3747.79
NSN 5	0.00	29.38	237.16	278.39
NSN 9	501.31	5.38	4.97	192.18
NSN 10	4919.62	340.40	1431.11	1268.53
NSN 11	8.88	7.95	16.73	20.68
NSN 12	0.37	54.76	259.53	88.05

best at forecasting with the lowest MSE in 9 cases. SBSS had the "best" MSE 5 times and simple exponential smoothing had the "best" MSE 1 time.

It should be noted that in a number of cases the differences between MSEs for different models were slight. For example, for the December forecasts of NSN 1 SBSS had the lowest MSE at 22.36, ARIMA was next best with 23.38, simple exponential smoothing was third best at 23.49, and Winters' seasonal exponential smoothing had the worst forecast with an MSE of 48.93. The first three models had a spread of only 1.13, roughly 5% of the lowest value, 22.36. This shows that in some cases several models had very similar performances.

Several comments about the forecasts for the SBSS and simple exponential smoothing models are in order. The SBSS was the best model only for forecasts from December and January when demands were higher and closer to the mean of all the demands and more periods were being forecast. The simpler models performed better when they could forecast close to the mean of the entire series. Also, simple exponential smoothing had nearly the same forecasts as the SBSS method in many, although not all cases (NSN 9 is a good example of the latter case). This is consistent with the notion that both the SBSS and simple exponential smoothing are simply modified moving averages.

Considering the difficulty with which ARIMA models are made, the methodology performed relatively poorly. In only

9 of 28 forecasts was it the best method. In comparison, the simplest models (SBSS and simple exponential smoothing) were "best" on 6 of the 28 forecasts.

Of the 9 forecasts in which ARIMA models excelled, four were the forecasts for NSN 5. This model, with AR 3 and 5 terms, MA 1 and 2 terms, and a regular differencing term, was one of the most complex developed in this study. In contrast, the simplest ARIMA model, an MA 1 developed for NSN 3, was worse than the Winters' model in all four forecasts for that NSN. Winters' seasonal exponential smoothing models also generated the best forecasts all four times for NSN 10, and again, the ARIMA model was relatively simple, an MA 1 and 2. In contrast, for NSN 9, Winters' was the best in two forecasts, SBSS and simple exponential smoothing were each best once, and ARIMA was never the best model, in spite of having two AR terms and one MA term. For NSNs 11 and 12, the ARIMA model was the best model in two of the forecasts. Winters' and SBSS were each best for one forecast of NSN 11, while SBSS was best for two forecasts of NSN 12. Finally, for NSN 1, Winters' was the best model in two forecasts, while ARIMA was best once and SBSS was best once. For these last 3 NSNs, the ARIMA models had either two MA or two AR terms. So, it appears that the more complex ARIMA models better forecast the hold-out data.

Several observations may be made concerning the relative performance of the models. First, several of the MSFs were quite close, such as the December forecast for NSN 11.

So, ARIMA did not perform as poorly as it might appear at first glance. Second, when ARIMA was well-fitted, as it apparently was in the case of NSN 5, the MSE was lower by one order of magnitude as compared to the other models, so when it was able to capture the demand data well, it excelled. Third, it must be remembered that the Box-Jenkins methodology works best with extensive data (60 months or better yet, 120 months). In Chapter III it was noted that the models were built with a bare minimum of data, which was artificially made continuous from two separate groups of data. Fourth, the exponential smoothing models used a slightly different set of data which was continuous. This too may have affected the results. Fifth, the demand patterns were not clearly seasonal, and with possible management influences changing demands from year to year, any model may have difficulty generating reasonably accurate forecasts.

Considering these factors, it is not surprising that the results were mixed. One fact is clear, however, Winters' and ARIMA models do a better job of forecasting demands that follow somewhat a seasonal demand pattern than do the SBSS and simple exponential smoothing models which tend to best forecast slowly changing constant levels of demand.

Conclusions

This chapter discussed the analysis of the data for seasonality and the results of the model building. The models were introduced, along with an analysis of whether or not like items had similar parameters in the simple and seasonal exponential models. Additionally the forecasts generated by the models were presented, along with an analysis of how each technique performed compared to the others.

The seasonality tests gave mixed results. Graphically, NSNs 1, 2, 3, 5, 9, 10, 11, and 12 showed some consistency of pattern with dual peak demands each year, while NSN 4 showed a plateau shaped high demand period. NSNs 6, 7, and 8 showed no discernable demand pattern.

The exponential smoothing models were evaluated to determine if one model could be used to forecast several like items. One could use a single simple exponential smoothing model to generate forecasts for the three sizes of mukluks and another model to generate forecasts for the three sizes of coats. In no cases could a single Winters' seasonal exponential smoothing model be used to forecast demands for different sizes of the same type item.

The evaluation of which model best forecast the hold-out data was also presented. Winters' seasonal exponential smoothing proved better than the ARIMA models. However, based on the small sample size, the data difficulties, and the closeness of the results this is certainly not a definitive conclusion.

V. Conclusions and Recommendations

Introduction

This chapter discusses how the results answer the research questions and presents some possible recommendations for both further study and action. Briefly, the study determined that Winters' seasonal exponential smoothing and ARIMA models forecast demands for the sample items better than the SBSS method of forecasting demands. Additionally, it was found that the Winters' seasonal exponential smoothing models gave better results than the ARIMA models.

Responses to Research Questions

Research Question 1. How does the SBSS currently address consumable seasonal demand items? The SBSS does not distinguish between items with seasonal demand patterns and those without. Rather, it uses a modified simple exponential smoothing technique to calculate future demands for all consumable items. Since simple exponential smoothing techniques tend to lag changing trends in demand and offer varying degrees of responsiveness to seasonal demand patterns they are not the best suited for seasonal demand patterns.

Research Question 2. What are alternative methods of addressing consumable seasonal demand items in the SBSS? Two primary alternative methods of addressing consumable seasonal demand items in the SBSS were studied: Winters' seasonal exponential smoothing models and the ARIMA models. Both forecast techniques are known for their ability to capture patterns missed by simpler moving average and simple exponential smoothing techniques. However, an argument for the use of either seasonal forecast model in the SBSS would be tempered by added complexity of either seasonal model with its associated data storage requirements.

Research Question 3. Do items currently identified as seasonal by personnel at the base-level actually display seasonal tendencies? Two responses to this question can be made depending on the criteria used to answer it. A graphical analysis showed the items identified as seasonal by base-level personnel have some, although not strong, seasonal demand characteristics. All twelve stock numbers studied had definitely lower summer demands compared to winter demands. However, the timing of peak annual demands and demand curve shapes differed from one year to another. Depending on the item, peak demand might occur in January one year, followed by relatively steady, relatively high demands. The following year, possibly because of weather, differing management policies, or some other reason, the peak demand might be one month later, with few demands in the surrounding months. This weakens the argument that demands are truly seasonal.

The other technique determining the presence of seasonality was to use the autocorrelation function and determine if an item's monthly demands from twelve months apart were correlated. The results of this test were essentially negative. Although, as was mentioned in Chapter 4, some of the items were close to having significant correlations between demands one year apart, the demand data was not clearly seasonal according to this test. A number of reasons can be given to account for this. Large organizational buys, management control of the items, the limited demand history available for study, fluctuating weather, institutional changes in requirements, low demand rates, and changing budgets all could have affected demands in a non-random fashion.

Research Question 4. Can demand for the items currently identified as seasonal by personnel at the base-level be better forecast using a model that incorporates seasonal demand pattern information, or the current SBSS model? Even with items that do not show strong seasonal patterns, using forecast methods which can compensate for, or incorporate seasonal demand pattern information, did improve the accuracy of forecasts as measured by MSE. Of 28 forecasts of 7 different NSNs the seasonal models (Winters' and ARIMA) had the lower MSE 22 times. In some cases there was little difference in the forecasts; in others the best model performed much better. In light of the surprisingly poor performance of the ARIMA models, and the difficulty of analyzing the data and creating the models, Winters' was a better model choice. The Winters' seasonal exponential smoothing models were the best in 13 of the 28 forecasts and much easier to develop.

Research Question 5. What method could be used by personnel at the base-level to identify items as seasonal and forecast demands for those items accordingly? Given sufficient demand data, a check of the autocorrelation function is relatively easily accomplished with a microcomputer program and can give consistent results. However, given current demand data storage requirements (essentially one year at the base level) any type of analysis of seasonality would be impossible until several (4 at an absolute minimum) years of demand data were collected for analysis. It would be possible to write into the supply computer a program that could automatically calculate the autocorrelation function and check at the 11th, 12th, and 13th lags for evidence of seasonality, and flag the item as seasonal, given sufficient demand data. To manually select items for review to determine if seasonality existed in the demand data would be impossible given the number of items in the average base supply account.

Recommendations

A number of possibilities exist for additional analysis and study. In addition, some general recommendations are made.

1. Recommend a follow-on study be accomplished with additional historical data. This could answer many

questions about the effect of the small data sample available and the effect of using non-sequential data in the ARIMA models. A comparison of both models and forecasting ability with additional data could prove informative.

2. Recommend a random sample of stock numbers, not previously identified as seasonal, be studied to determine if seasonal techniques would be useful in forecasting demands and if items not flagged as seasonal exhibit seasonal demand patterns. This would be facilitated by the development of a Fortran computer program that would take transaction history data tapes and have as a product useable monthly demand data and a monthly SBSS forecast for comparison purposes.

3. Recommend AFLMC/LGS study the feasibility of storing demand data in a more accessible format and for a longer duration in the SBSS. Data is much more likely to be used when it is accessible. As transaction histories are accumulated, samples of demand data fitting various criteria could be extracted and analyzed on microcomputer-based programs at base-level accounts.

4. Recommend additional research be done in the area of using Winters' exponential smoothing or another seasonal model which could better forecast seasonal demands on consumable items due to end-of-year funding constraints, annual weather effects on aircraft parts, and annual exercise patterns.

5. Recommend future studies between the relationship of more complex ARIMA models and SBSS demand data be evaluated to determine if one to three MA or AR term models are less capable of forecasting demand than Winters' seasonal exponential smoothing.

Conclusions

This study, in spite of the small sample size, and possible data problems, demonstrated that seasonal demand items are better forecast using models which account for seasonal demands. Although the data requirements for creating and using seasonal models are more extensive than for simple exponential smoothing or moving average models, with the current reduced costs of storing data and increased computer capabilities, the use of seasonal models is well worth further investigation. The potential cost savings resulting from better forecasts of consumable items certainly warrant further investigations into this area.

Attachment 1: Items Selected for Study

	STOCK NUMBER	NOMENCLATURE	LIKE ITEM GROUP
NSN1	8430002690100	BOOT, MUKLUK LARGE	(A)
NSN2	8415003761661	PARKA.ECW GRN X-SMA	
NSN3	8440001536717	SOCKS.MENS C/W NA10	(B)
NSN4	8415007822935	COAT MANS SML-SHOR	(C)
NSN5	8415007822938	COAT MAN MED SHT	(C)
NSN6	8440001536721	SOCKS,MENS C/W NA14	(B)
NSN7	8415007822940	COAT MAN MED LG 33	(C)
NSN8	8415002702014	UNDERSHIRT EX WEA L	
NSN9	8415002687872	GLOVE SHELLS, CW SZ2	
NSN10	8440002614897	SOCKS.MEN.CW.NAUTR9	(B)
NSN11	8430002690098	BOOT MUKLUK MANS SM	(A)
NSN12	8430002690099	BOOT MUKLUK MED	(A)

Attachment 2: Sample Data Extraction Fortran Program and Data Tape Schema

```
C
C     DEFINE VARIABLES
C
      CHARACTER*2 TTPC
      CHARACTER*3 DIC
      CHARACTER*4 DOLD.DOLT
      CHARACTER*6 TRANSD.ACTQTY
      CHARACTER*13 STKNUM.SNREQ.STOCKN
      CHARACTER*14 DOCNUM
      CHARACTER*20 FILENM
      CHARACTER*121 DUMMY
      INTEGER*4 ICOUNT.OCOUNT

C
C  SET RECORD COUNTERS
C
      ICOUNT=0
      OCOUNT=0
C
C  GET INPUT FILE NAME AND OPEN FILE
C
    5 WRITE(*.900)
  900 FORMAT(' ENTER INPUT FILE NAME: ',$)
      READ(*,905) FILENM
  905 FORMAT(A20)
      OPEN(1,FILE=FILENM.STATUS='OLD')
C
C  GET OUTPUT FILE NAME AND OPEN FILE
C
   10 WRITE(*.910)
  910 FORMAT(' ENTER OUTPUT FILE NAME: '.$)
      READ(*.915) FILENM
  915 FORMAT(A20)
C
C  GET STOCK NUMBER FOR SEARCH
C
      WRITE(*.917)
  917 FORMAT(' ENTER STOCK NUMBER: '.$)
      READ(*.918) STOCKN
  918 FORMAT(A13)
C
C  READ A RECORD
C
      OPEN(2.FILE=FILENM.STATUS='NEW')
   20 READ(1.920.END=999)STKNUM.DUMMY.DIC.DUMMY.
     &     DOCNUM.DOLD.DUMMY.TRANSD.DUMMY.
     &     ACTQTY.DUMMY.DOLT.DUMMY.TTPC.
     &     DUMMY.SNREQ
      ICOUNT=ICOUNT+1
```

```
 920  FORMAT(A13.A13.A3.A13.A14.A4.A6.A6.A9.
     &     A6.A8.A4.A8.A2,A16.A13)
C
C  STOCK NUMBER SELECTION LIST
C
      IF(STKNUM.EQ.STOCKN) THEN
      WRITE(2.940)STKNUM.DIC.DOCNUM.DOLD.
     &     TRANSD.ACTQTY.DOLT.TTPC.SNREQ
 940  FORMAT(1X.A13.2X.A3.2X.A14.2X.A4.2X.
     &     A6.2X.A6,2X.A4.2X.A2.1X.A13)
      OCOUNT=OCOUNT+1
      ENDIF
C
      GOTO 20
C
 999  WRITE(2,950)ICOUNT.OCOUNT
 950  FORMAT(' INPUT RECORDS READ = '.I5.
     &       '     OUTPUT RECORDS WRITTEN = '.I5)
      CLOSE(1)
      CLOSE(2)
      STOP
      END
```

Data Tape Schema (27)

POS. NO.	SECTOR POS.	LA	DESCRIPTION
15	1-15	SN	Stock Number
2	16-17	WS	System Designator
1	18	AC	Sran Type
3	19-21	ER	ERRCD
1	22	ME	Stockage Priority Code
2	23-24	PY	Issue Priority
1	25	TX	TEX
1	26	PM	Demand Code
3	27-29	ID	DIC-TRIC
2	30-31	UI	Unit-of-Issue
2	32-33	FC	Fund Code
6	34-39	SA	Sup-Requisitioner
3	40-42	RI	Routing Identifier
14	43-56	DN	Document Number
4	57-60	LD	DOLD
6	61-66	EB	Ending Balance
6	67-72	DT	Transaction Date
6	73-78	TN	Transaction Ser Nbr
3	79-81	FI	FIA Trans
6	82-87	QY	Action Qty
8	88-95	XP	Extended Cost
4	96-99	LT	DOLT
3	100-102	ST	Status or Advice Code
1	103		Blank
3	104-106	OP	Output Terminal
1	107	FO	MAT. CAT. SOS Code
2	108-109	PE	TTPC
1	110	IN	Print Punch. Old TR
1	111	BJ	Budget Code
14	112-125	MF	Mark-For
15	126-140	SR	SN Requested
19	141-159	NM	Noun
5	160-164	MC	MFG's Code
1	165	RW	Reason-Why-Code
7	166-172		Blank
1	173	RC	Reporting Code
1	174	IX	LEX
19	175-193		Blank

Attachment 3: Original Data
(Blank rows indicate no data originally available)

DATE	NSN1	NSN2	NSN3	NSN4	NSN5	NSN6
JAN 82						
FEB	0	0	0	0	0	0
MAR	2	0	48	20	23	0
APR	3	0	23	32	28	0
MAY	0	0	0	0	0	0
JUN	0	0	20	4	4	0
JUL	0	0	2	1	7	0
AUG	8	0	90	5	7	0
SEP	0	0	197	18	22	14
OCT	13	4	1040	83	66	100
NOV	104	0	206	69	0	13
DEC	0	0	0	0	0	0
JAN 83	101	4	267	23	68	0
FEB	120	3	112	42	8	0
MAR						
APR	0	0	186	10	12	0
MAY	0	0	8	4	5	5
JUN	0	0	15	2	7	0
JUL	0	0	2	2	4	0
AUG						
SEP	0	0	160	14	10	0
OCT	0	0	0	13	26	1
NOV	0	0	47	5	12	3
DEC	0	3	20	26	17	14
JAN 84						
FEB						
MAR						
APR						
MAY						
JUN						
JUL						
AUG						
SEP						
OCT						
NOV						
DEC						
JAN 85						
FEB						
MAR						
APR						
MAY						
JUN						
JUL						
AUG						
SEP						
OCT						
NOV						
DEC						

DATE	NSN1	NSN2	NSN3	NSN4	NSN5	NSN6
JAN 86						
FEB						
MAR						
APR						
MAY						
JUN						
JUL						
AUG	3	1	9	9	1	0
SEP	55	1	141	30	31	0
OCT	6	6	146	13	31	2
NOV						
DEC						
JAN 87						
FEB	37	8	211	44	58	21
MAR						
APR	17	6	42	22	21	4
MAY	1	0	80	3	2	0
JUN	0	0	4	0	1	0
JUL	0	0	3	2	3	2
AUG	5	0	98	8	5	0
SEP	2	0	9	3	3	0
OCT	32	2	325	19	16	93
NOV	11	3	533	4	107	20
DEC	4	0	0	16	7	0
JAN 88						
FEB	47	2	32	18	139	2
MAR	6	3	38	12	4	9
APR	0	1	13	12	0	0
MAY	0	0	22	6	4	0
JUN	0	0	4	0	1	0
JUL	0	0	0	1	1	3
AUG	1	0	40	5	3	14
SEP	6	3	236	13	10	57
OCT	27	9	154	13	6	9
NOV	4	0	74	1	13	2
DEC	8	1	73	8	6	29
JAN 89	7	0	77	5	5	0
FEB	10	1	63	6	1	2
MAR	9	0	49	1	0	0
APR	5	1	25	1	1	0

DATE	NSN7	NSN8	NSN9	NSN10	NSN11	NSN12
JAN 82						
FEB	0	0	0	0	0	0
MAR	24	111	30	45	10	13
APR	10	76	8	7	2	2
MAY	0	0	0	0	0	0
JUN	3	5	7	10	6	6
JUL	1	8	31	0	0	0
AUG	5	220	34	81	5	10
SEP	28	216	24	207	1	0
OCT	71	3010	29	310	7	23
NOV	20	355	53	159	54	105
DEC	0	0	0	0	0	0
JAN	10	515	59	70	28	20
FEB 83	27	243	105	311	1	136
MAR	6	106	7	41	1	0
MAY	1	12	59	0	0	0
JUN	9	11	9	1	0	0
JUL	0	5	3	18	0	0
AUG	11	28	19	158	0	0
OCT	15	1008	30	127	14	168
NOV	2	6	0	12	0	0
DEC	14	249	18	138	1	51
JAN 84						
FEB						
MAR						
APR						
MAY						
JUN						
JUL						
AUG						
SEP						
OCT						
NOV						
DEC						
JAN 85						
FEB						
MAR						
APR						
MAY						
JUN						
JUL						
AUG						
SEP						
OCT						
NOV						
DEC						
JAN 86						
FEB						
MAR						
APR						

DATE	NSN7	NSN8	NSN9	NSN10	NSN11	NSN12
MAY						
JUN						
JUL						
AUG	0	12	0	9	2	6
SEP	30	342	92	107	18	66
OCT	14	265	15	80	12	50
NOV						
DEC						
JAN 87						
FEB	18	357	12	129	37	79
MAR						
APR	3	49	14	61	2	9
MAY	2	9	18	6	2	4
JUN	1	14	2	9	1	0
JUL	0	91	6	6	1	2
AUG	5	216	3	80	1	11
SEP	2	23	10	7	5	3
OCT	11	158	9	69	30	44
NOV	11	590	1	206	4	22
DEC	1	86	23	78	0	0
JAN 88						
FEB	95	27	2	18	0	68
MAR	3	153	4	62	5	24
APR	2	22	0	2	0	3
MAY	4	55	4	4	28	4
JUN	2	2	1	4	0	1
JUL	0	2	1	5	0	1
AUG	2	42	2	29	0	0
SEP	15	385	56	100	27	42
OCT	5	412	72	277	30	65
NOV	4	2	4	2	14	25
DEC	3	502	13	17	6	11
JAN 89	2	873	52	81	6	23
FEB	1	161	12	33	4	18
MAR	0	54	2	28	4	31
APR	1	47	3	17	5	13

Attachment 4: Exponential Smoothing Data
(Underline marks values created using Delphi technique)

DATE	NSN1	NSN2	NSN3	NSN4	NSN5	NSN6
AUG 86	3	1	9	9	1	0
SEP	55	1	141	30	31	0
OCT	6	6	146	13	31	2
NOV	18	3	134	22	22	9
DEC	23	3	140	33	19	12
JAN 87	39	3	153	36	38	13
FEB	37	8	211	44	58	21
MAR	18	6	92	22	26	10
APR	17	6	42	22	21	4
MAY	1	0	80	3	2	0
JUN	0	0	4	0	1	0
JUL	0	0	3	2	3	2
AUG	5	0	98	8	5	0
SEP	2	0	9	3	3	0
OCT	32	2	325	19	16	93
NOV	11	3	533	4	107	20
DEC	4	0	0	16	7	0
JAN 88	24	2	64	16	39	1
FEB	47	2	32	18	139	2
MAR	6	3	38	12	4	9
APR	0	1	13	12	0	0
MAY	0	0	22	6	4	0
JUN	0	0	4	0	1	0
JUL	0	0	0	1	1	3
AUG	1	0	40	5	3	14
SEP	6	3	236	13	10	57
OCT	27	9	154	13	6	9
NOV	4	0	74	1	13	2
DEC	8	1	73	8	6	29
JAN 89	7	0	77	5	5	0
FEB	10	1	63	6	1	2
MAR	9	0	49	1	0	0
APR	5	1	25	1	1	0

DATE	NSN7	NSN8	NSN9	NSN10	NSN11	NSN12
AUG 86	0	12	0	9	2	6
SEP	30	342	92	107	18	66
OCT	14	265	15	80	12	50
NOV	14	182	11	53	10	58
DEC	18	115	16	31	9	60
JAN 87	18	313	27	105	20	63
FEB	18	357	12	129	37	79
MAR	8	154	15	76	19	52
APR	3	49	14	61	2	9
MAY	2	9	18	6	2	4
JUN	1	14	2	9	1	0
JUL	0	91	6	6	1	2
AUG	5	216	3	80	1	11
SEP	2	23	10	7	5	3
OCT	11	158	9	69	30	44
NOV	11	590	1	206	4	22
DEC	1	86	23	78	0	0
JAN 88	30	180	22	55	16	39
FEB	95	27	2	18	0	68
MAR	3	153	4	62	5	24
APR	2	22	0	2	0	3
MAY	4	55	4	4	28	4
JUN	2	2	1	4	0	1
JUL	0	2	1	5	0	1
AUG	2	42	2	29	0	0
SEP	15	385	56	100	27	42
OCT	5	412	72	277	30	65
NOV	4	2	4	2	14	25
DEC	3	502	13	17	6	11
JAN 89	2	873	52	81	11	23
FEB	1	161	12	33	4	18
MAR	0	54	2	28	4	31
APR	1	47	3	17	5	13

Attachment 5: Box-Jenkins Data

(Underline marks values created using Delphi technique)

DATE	NSN1	NSN2	NSN3	NSN4	NSN5	NSN6
JAN 82	25	3	85	14	25	1
FEB	0	0	0	0	0	0
MAR	2	0	48	20	23	0
APR	3	0	23	32	28	0
MAY	0	0	0	0	0	0
JUN	0	0	20	4	4	0
JUL	0	0	2	1	7	0
AUG	8	0	90	5	7	0
SEP	0	0	197	18	22	14
OCT	13	4	1040	83	66	100
NOV	104	0	206	69	0	13
DEC	0	0	0	0	0	0
JAN 83	101	4	267	23	68	0
FEB	120	3	112	42	8	0
MAR	15	1	118	25	11	1
APR	0	0	186	10	12	0
MAY	0	0	8	4	5	5
JUN	0	0	15	2	7	0
JUL	0	0	2	2	4	0
AUG	1	0	71	8	6	5
SEP	0	0	160	14	10	0
OCT	0	0	0	13	26	1
NOV	0	0	47	5	12	3
DEC	0	3	20	26	17	14
JAN 87	39	3	153	36	38	13
FEB	37	8	211	44	58	21
MAR	18	6	92	22	26	10
APR	17	6	42	22	21	4
MAY	1	0	80	3	2	0
JUN	0	0	4	0	1	0
JUL	0	0	3	2	3	2
AUG	5	0	98	8	5	0
SEP	2	0	9	3	3	0
OCT	32	2	325	19	16	93
NOV	11	3	533	4	107	20
DEC	4	0	0	16	7	0
JAN 88	24	2	64	16	39	1
FEB	47	2	32	18	139	2
MAR	6	3	38	12	4	9
APR	0	1	13	12	0	0
MAY	0	0	22	6	4	0
JUN	0	0	4	0	1	0
JUL	0	0	0	1	1	3
AUG	1	0	40	5	3	14
SEP	6	3	236	13	10	57
OCT	27	9	154	13	6	9
NOV	4	0	74	1	13	2
DEC	8	1	73	8	6	29

DATE	NSN1	NSN2	NSN3	NSN4	NSN5	NSN6
JAN 89	7	0	77	5	5	0
FEB	10	1	63	6	1	2
MAR	9	0	49	1	0	0
APR	5	1	25	1	1	0

	NSN7	NSN8	NSN9	NSN10	NSN11	NSN12
JAN 82	11	205	31	73	15	13
FEB	0	0	0	0	0	0
MAR	24	111	30	45	10	13
APR	10	76	8	7	2	2
MAY	0	0	0	0	0	0
JUN	3	5	7	10	6	6
JUL	1	8	31	0	0	0
AUG	5	220	34	81	5	10
SEP	28	216	24	207	1	0
OCT	71	3010	29	310	7	23
NOV	20	355	53	159	54	105
DEC	0	0	0	0	0	0
JAN 83	10	515	59	70	28	20
FEB	27	243	105	311	1	136
MAR	13	140	45	64	9	32
APR	6	106	7	41	1	0
MAY	1	12	59	0	0	0
JUN	9	11	9	1	0	0
JUL	0	5	3	18	0	0
AUG	4	38	10	64	1	3
SEP	11	28	19	158	0	0
OCT	15	1008	30	127	14	168
NOV	2	6	0	12	0	0
DEC	14	249	18	138	1	51
JAN 87	18	313	27	105	20	63
FEB	18	357	12	129	37	79
MAR	8	154	15	76	19	52
APR	3	49	14	61	2	9
MAY	2	9	18	6	2	4
JUN	1	14	2	9	1	0
JUL	0	91	6	6	1	2
AUG	5	216	3	80	1	11
SEP	2	23	10	7	5	3
OCT	11	158	9	69	30	44
NOV	11	590	1	206	4	22
DEC	1	86	23	78	0	0
JAN 88	30	163	22	55	16	39
FEB	95	27	2	18	0	68
MAR	3	153	4	62	5	24
APR	2	22	0	2	0	3
MAY	4	55	4	4	28	4
JUN	2	2	1	4	0	1
JUL	0	2	1	5	0	1
AUG	2	42	2	29	0	0
SEP	15	385	56	100	27	42

DATE	NSN7	NSN8	NSN9	NSN10	NSN11	NSN12
OCT	5	412	72	277	30	65
NOV	4	2	4	2	14	25
DEC	3	502	13	17	6	11
JAN 89	2	873	52	81	6	23
FEB	1	161	12	33	4	18
MAR	0	54	2	28	4	31
APR	1	47	3	17	5	13

Attachment 6: Box-Jenkins Forecast
Demand Data Plots

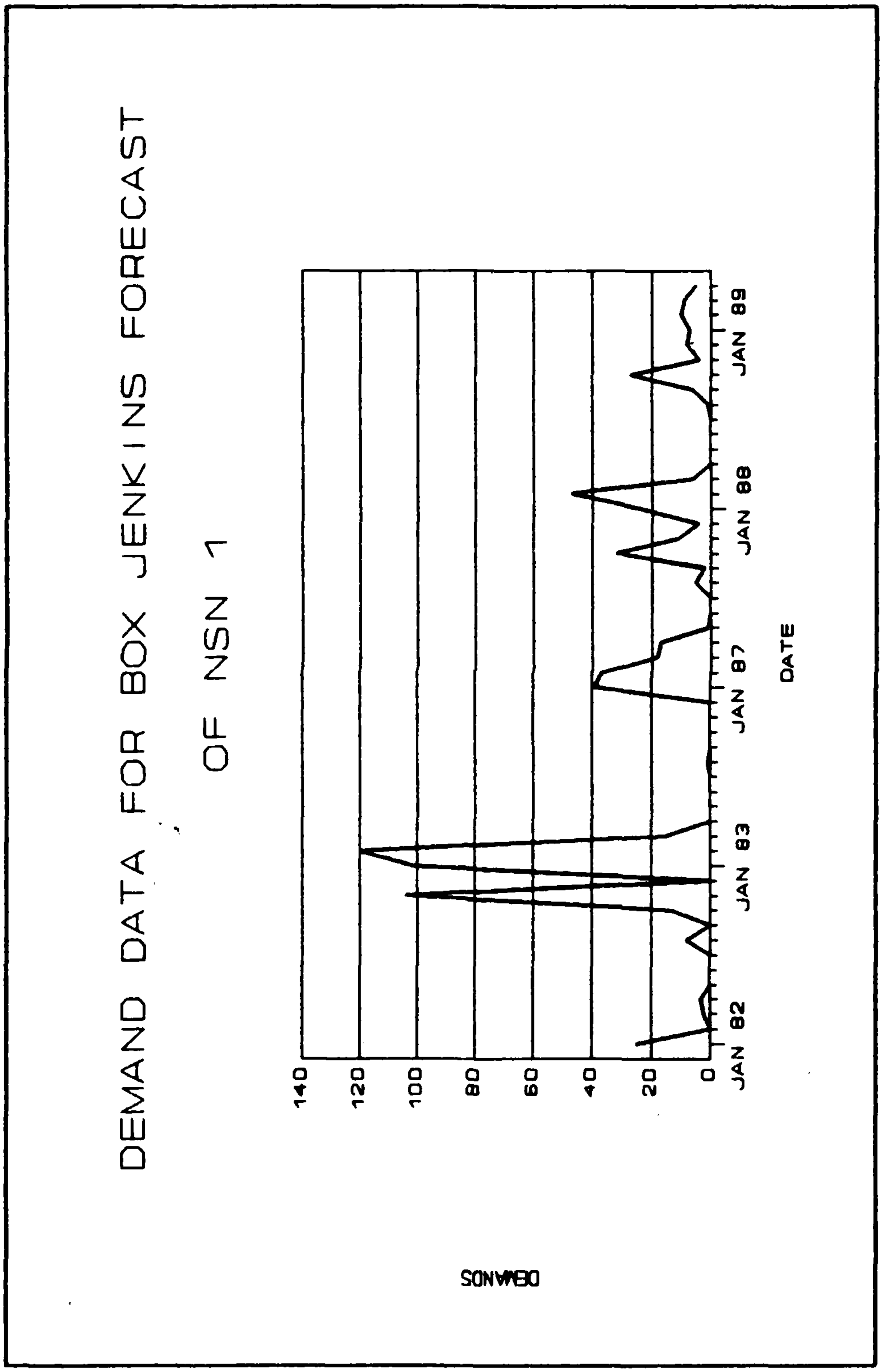

Figure 26. Box-Jenkins Forecast Demand Data for NSN 1

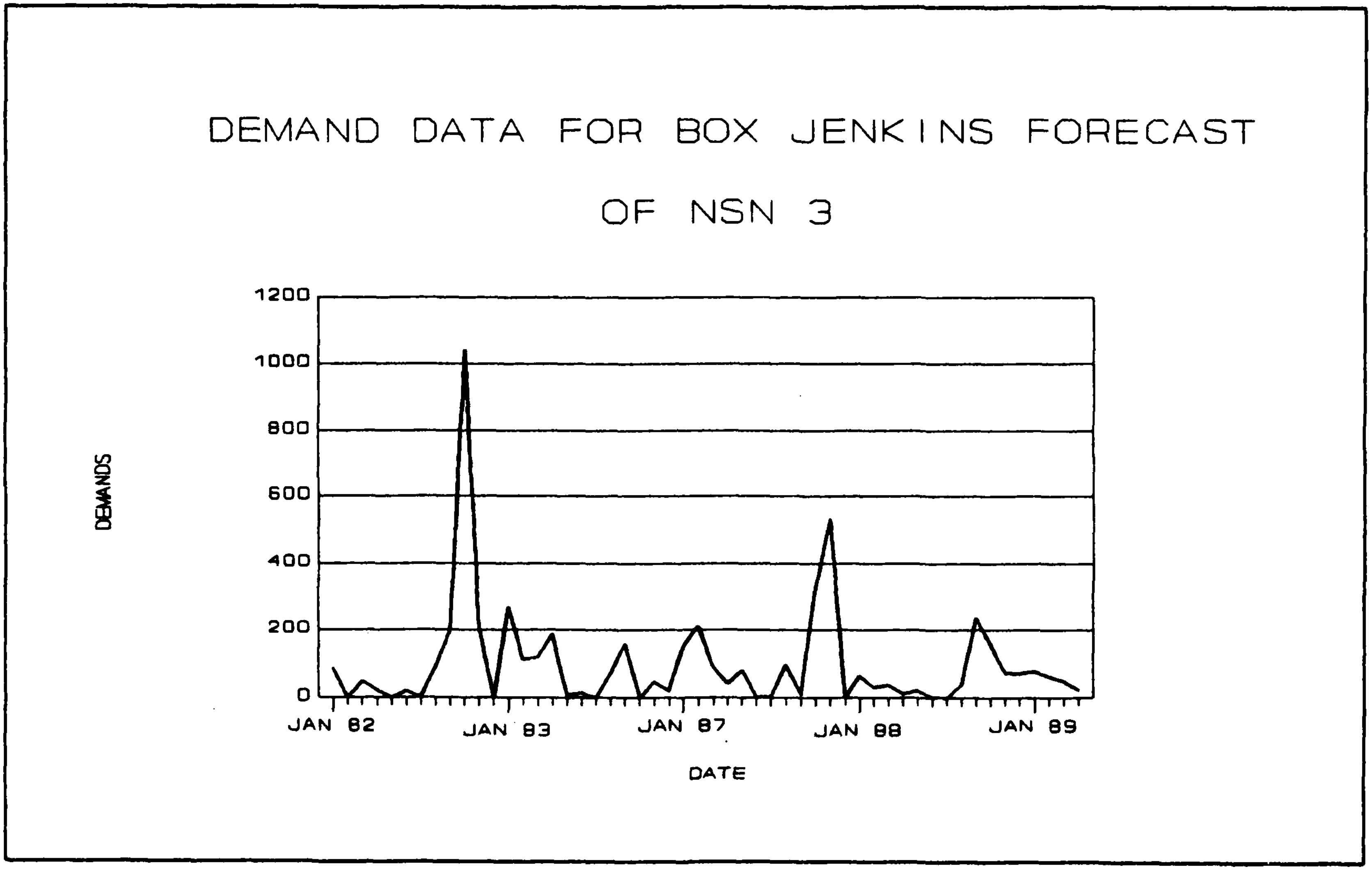

Figure 27. Box-Jenkins Forecast Demand Data for NSN 3

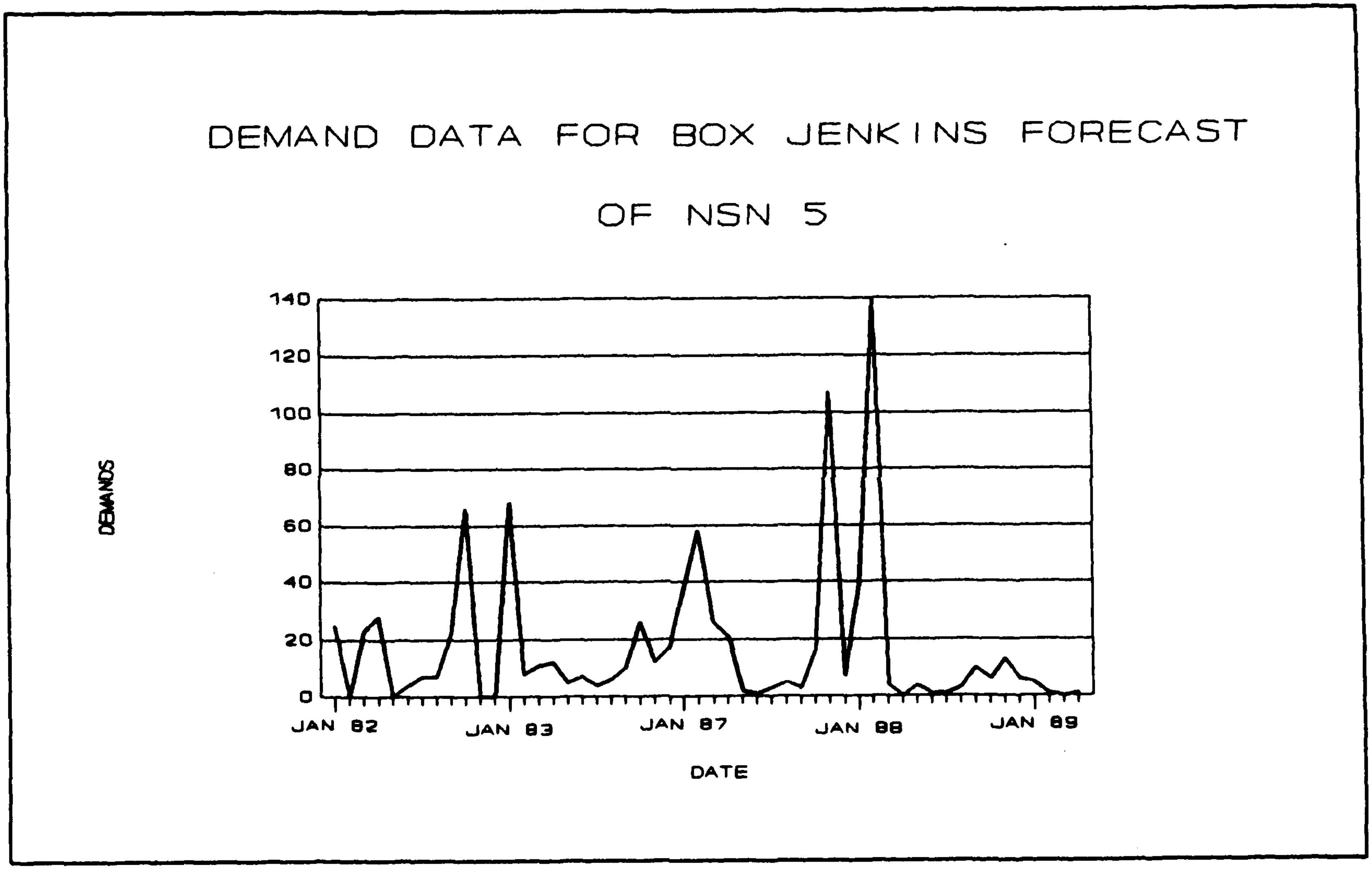

Figure 28. Box-Jenkins Forecast Demand Data for NSN 5

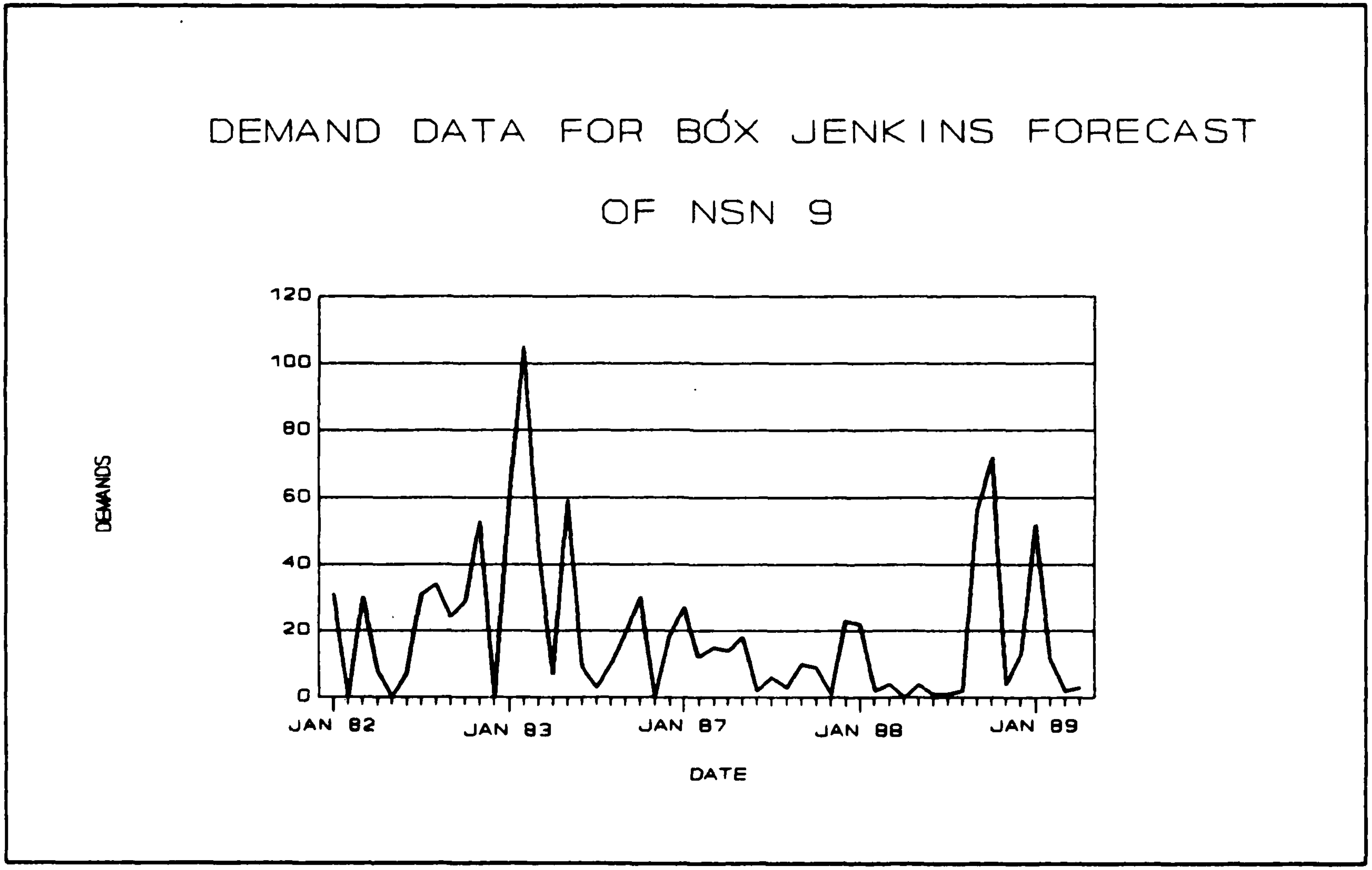

Figure 29. Box-Jenkins Forecast Demand Data for NSN 9

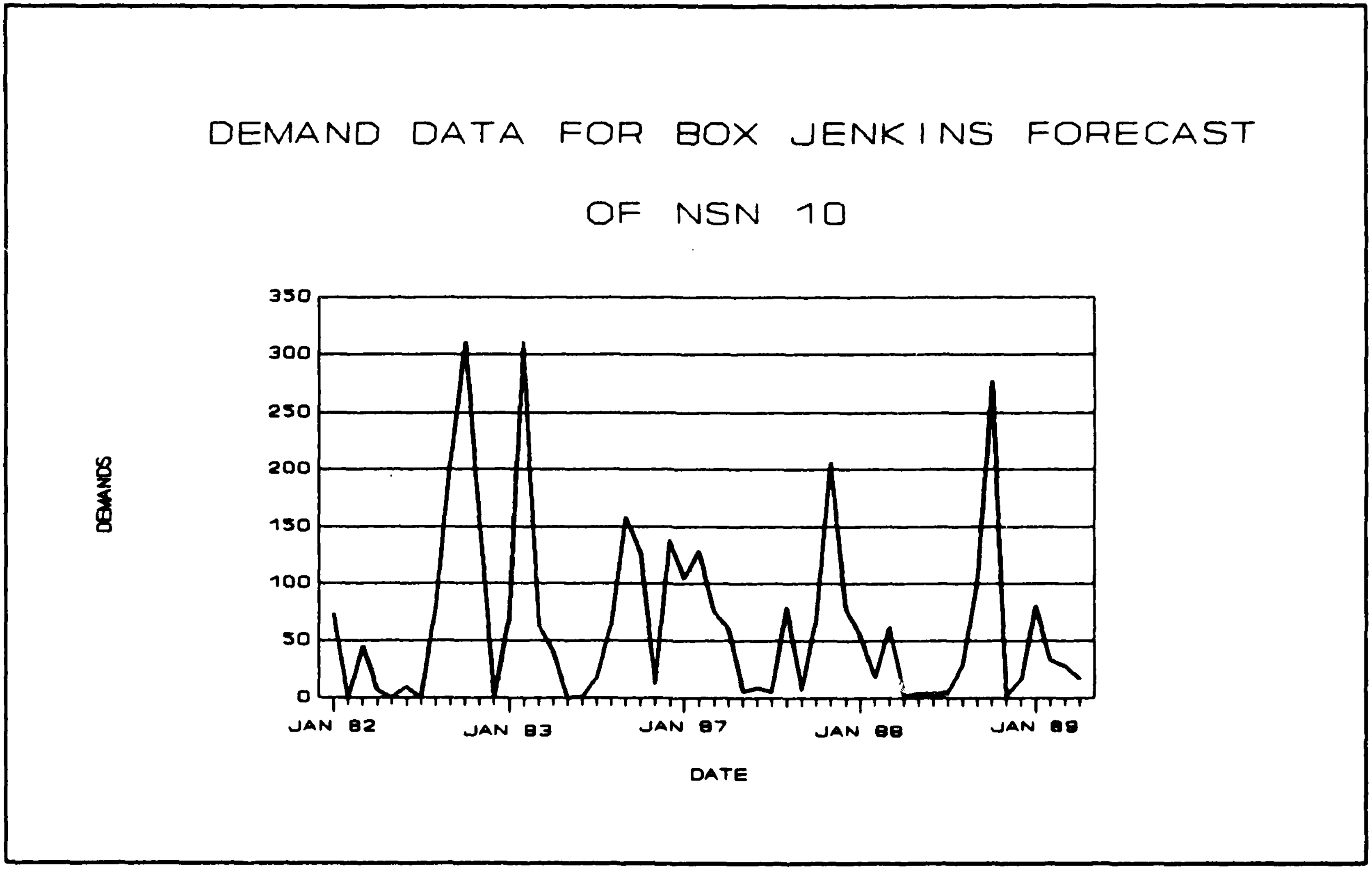

Figure 30. Box-Jenkins Forecast Demand Data for NSN 10

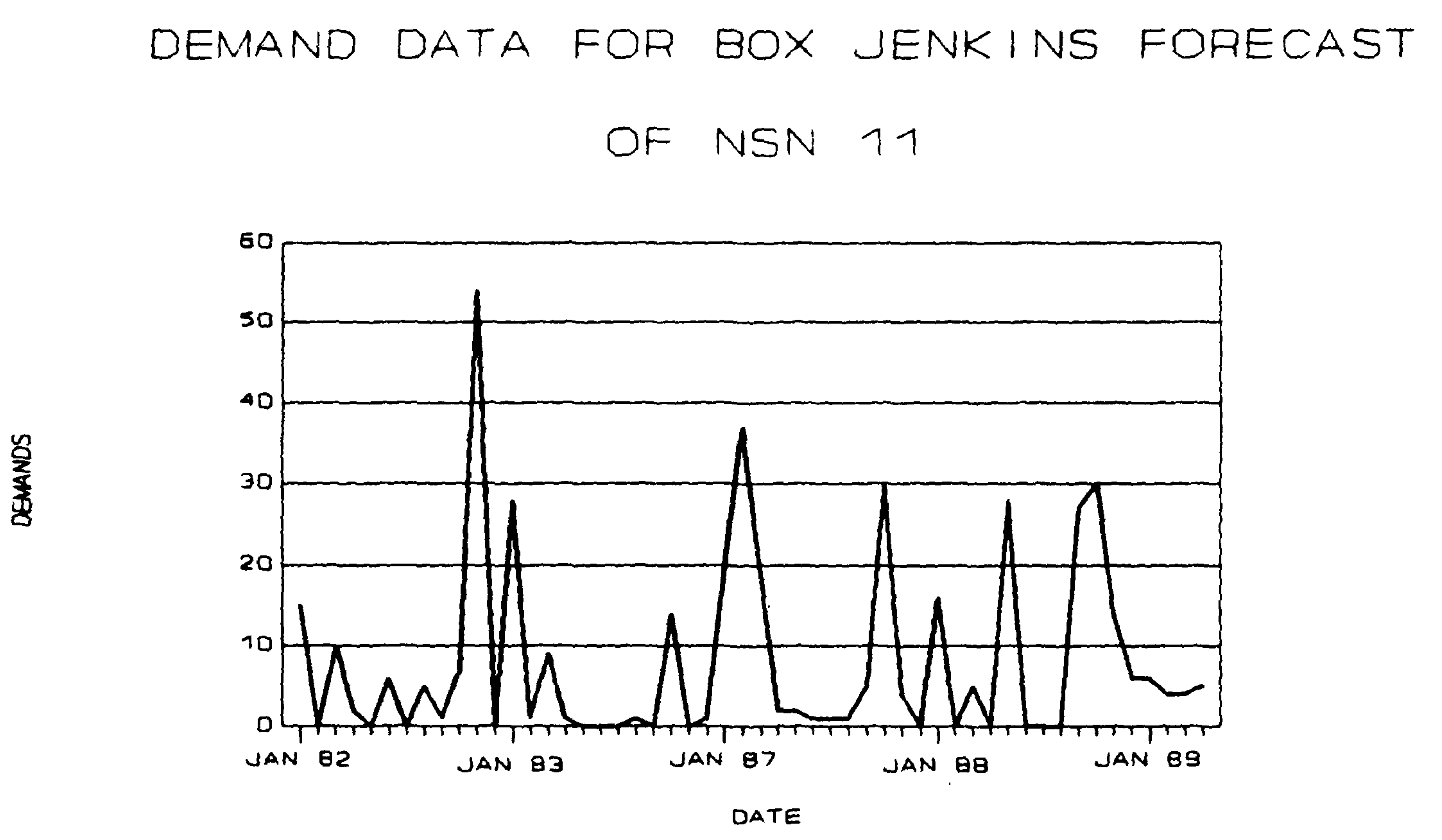

Figure 31. Box-Jenkins Forecast Demand Data for NSN 11

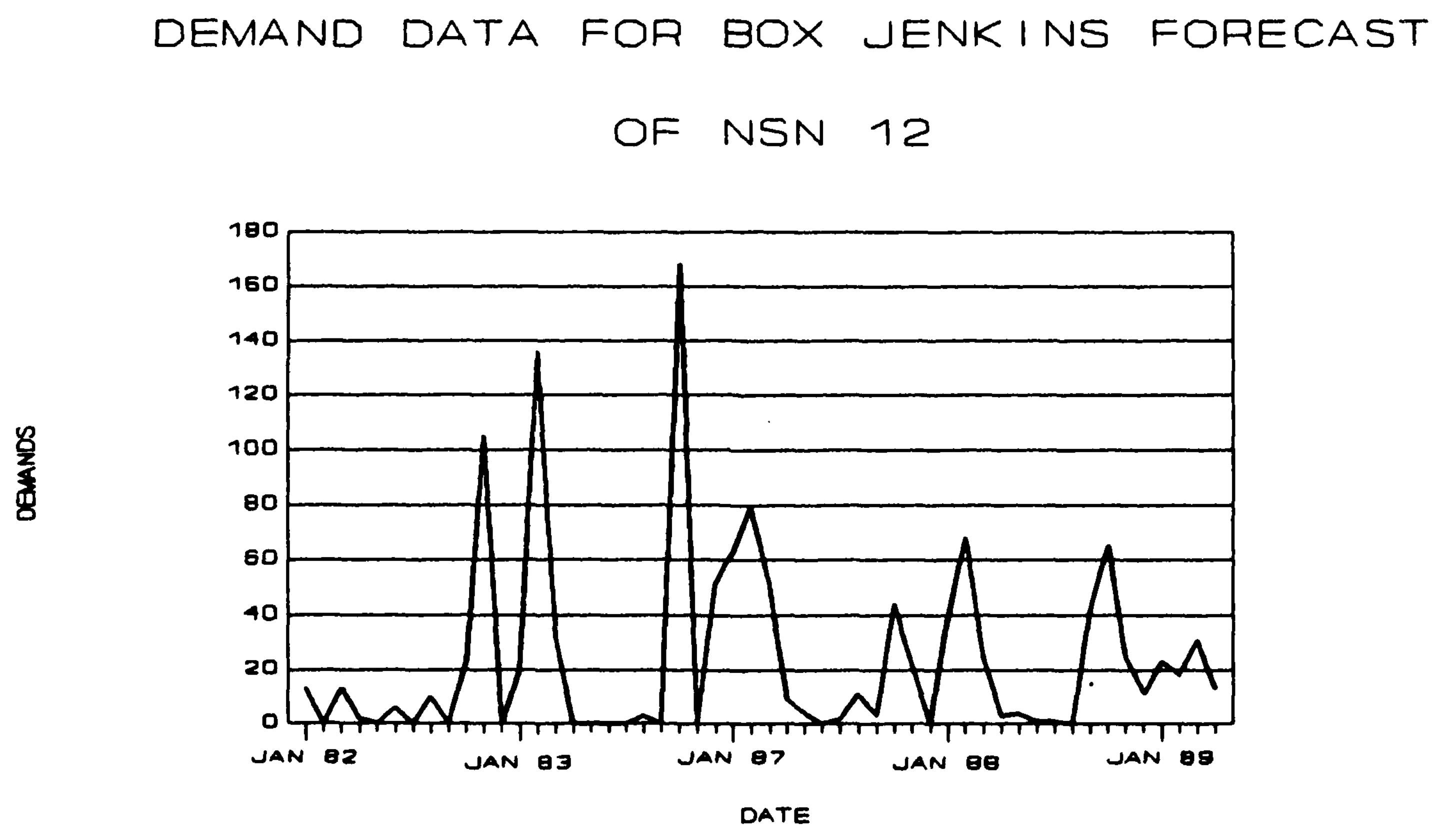

Figure 32. Box-Jenkins Forecast Demand Data for NSN 12

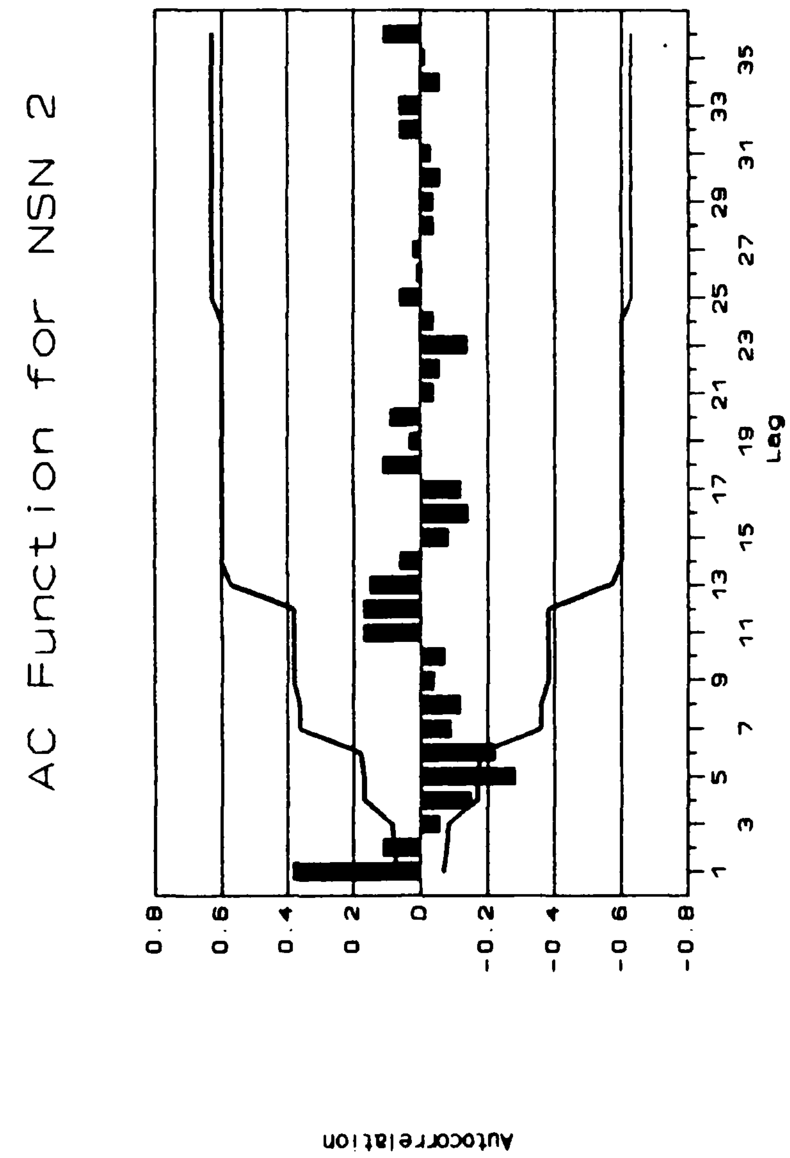

Figure 33. Autocorrelation Function for NSN 2

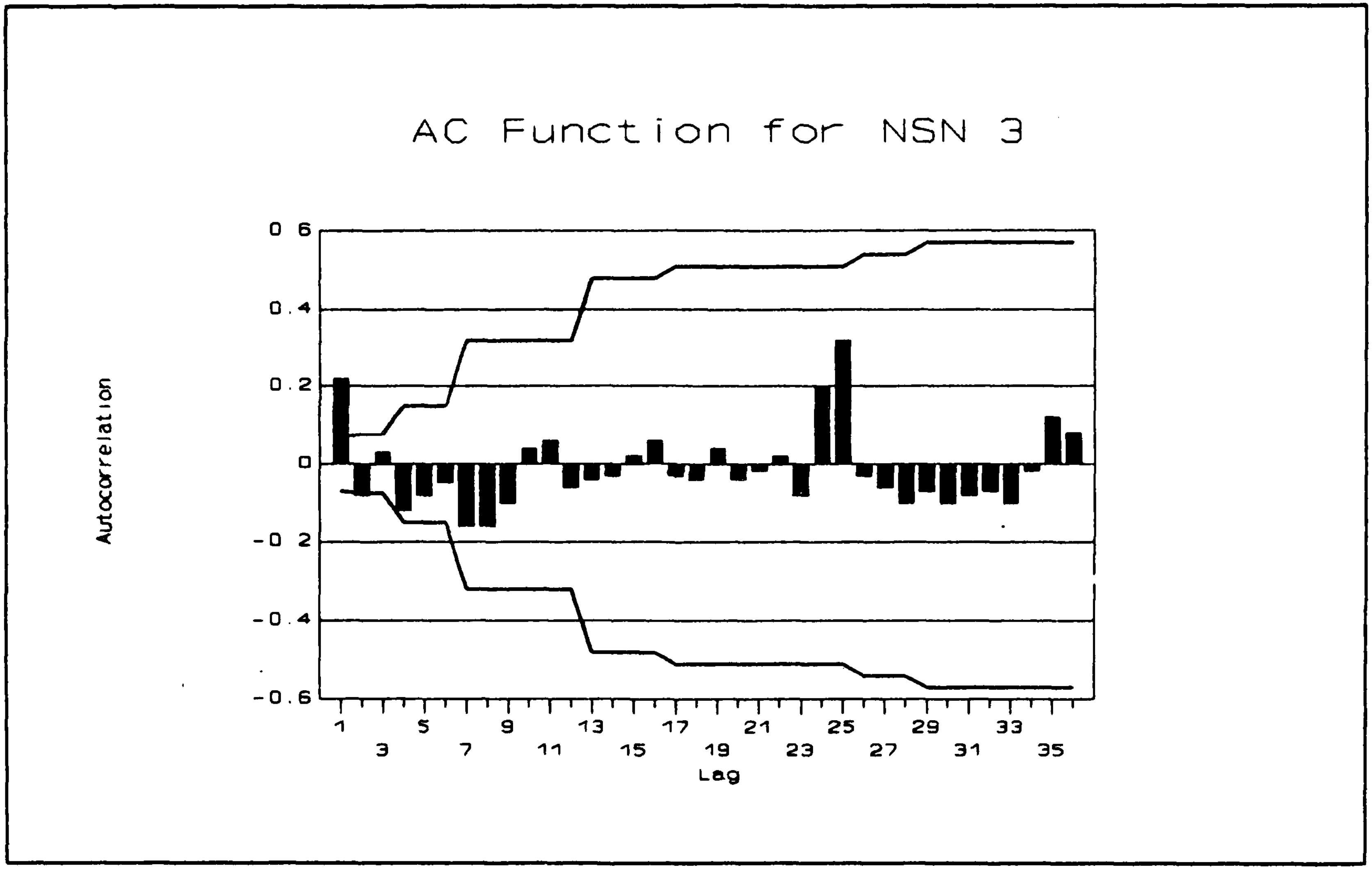

Figure 34. Autocorrelation Function for NSN 3

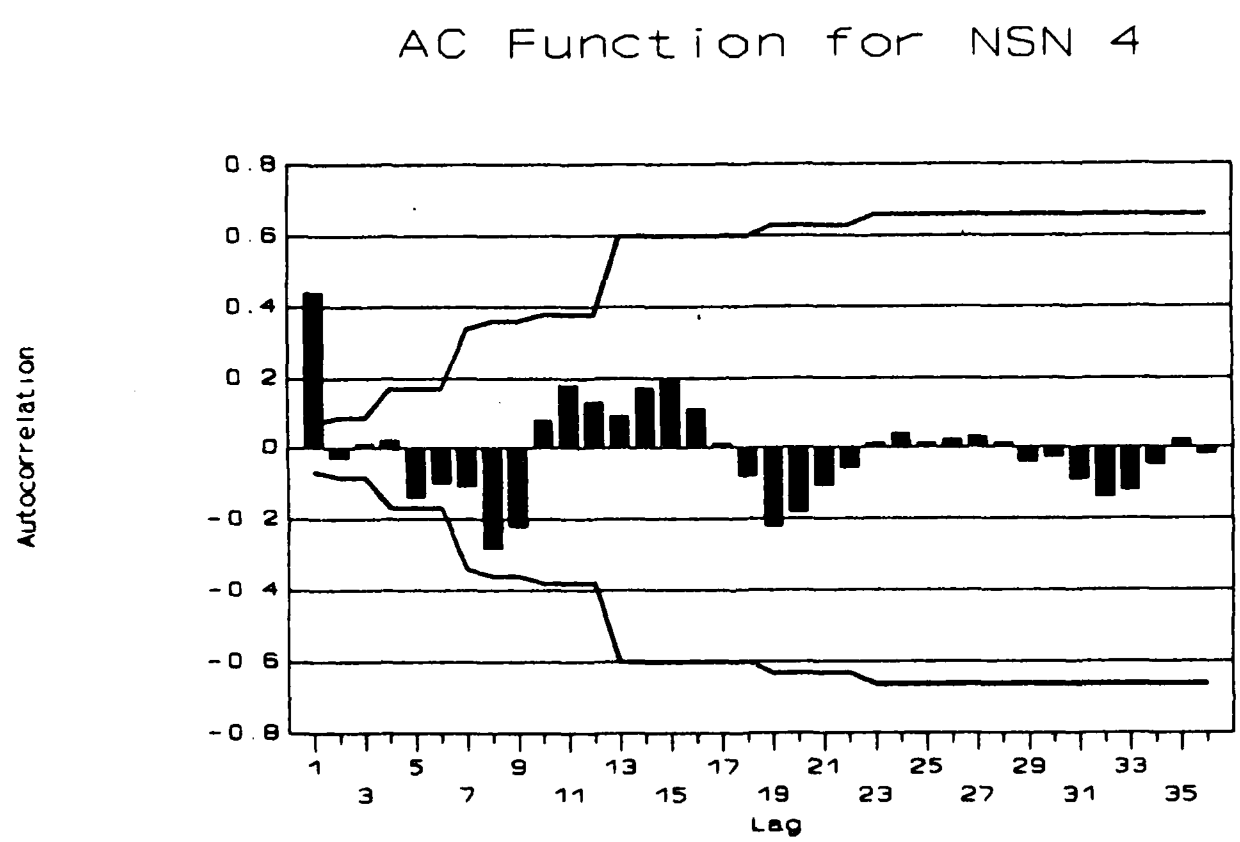

Figure 35. Autocorrelation Function for NSN 4

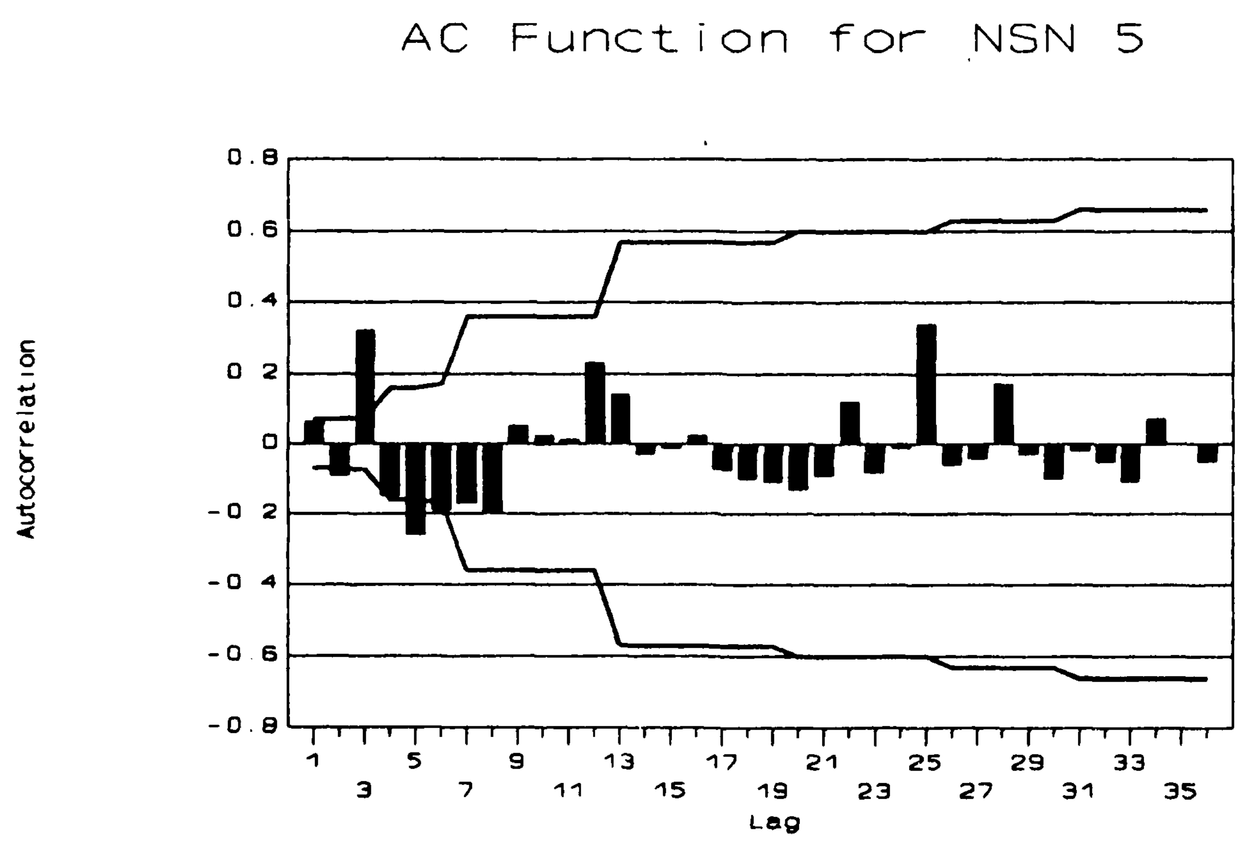

Figure 36. Autocorrelation Function for NSN 5

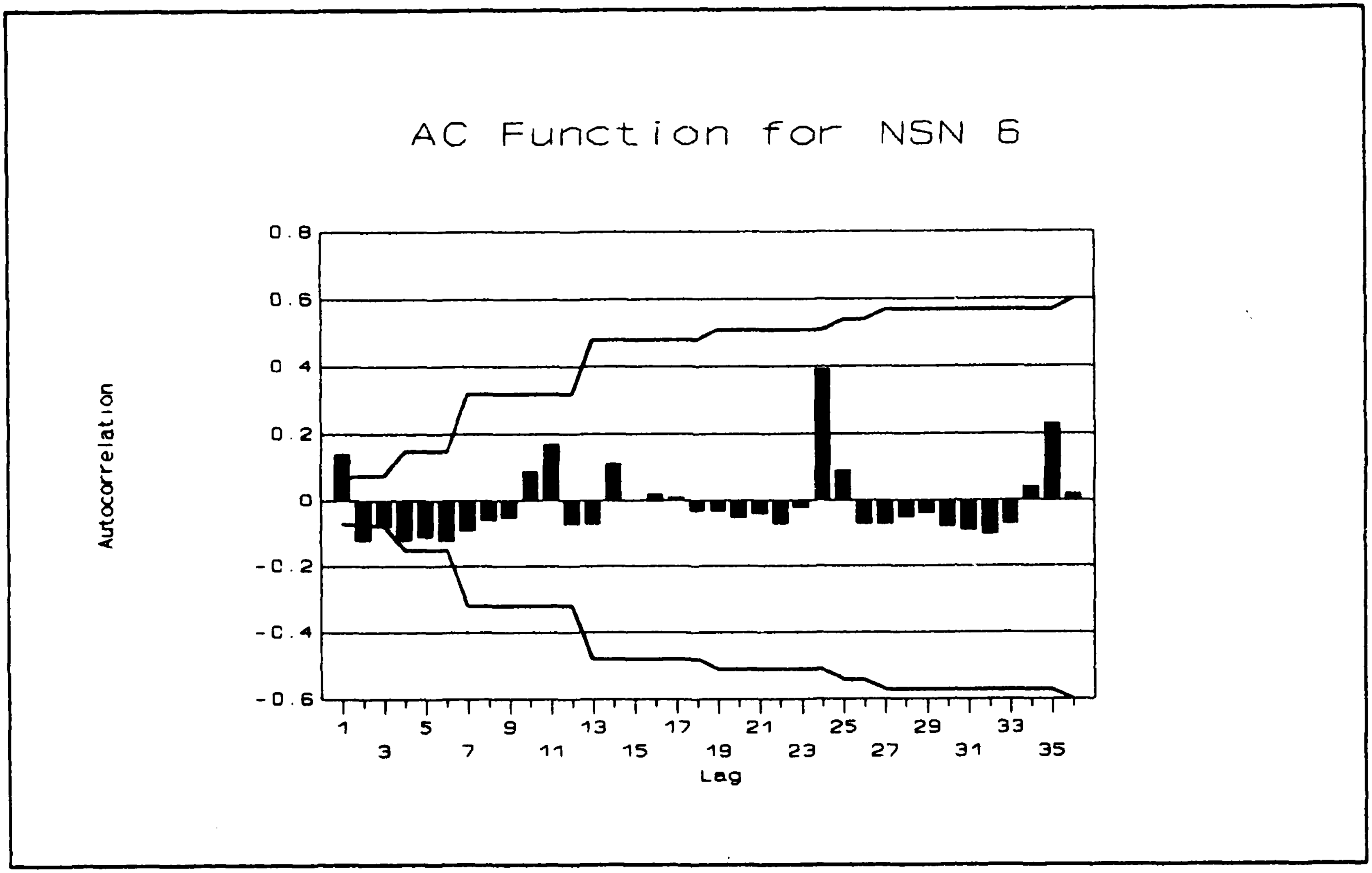

Figure 37. Autocorrelation Function for NSN 6

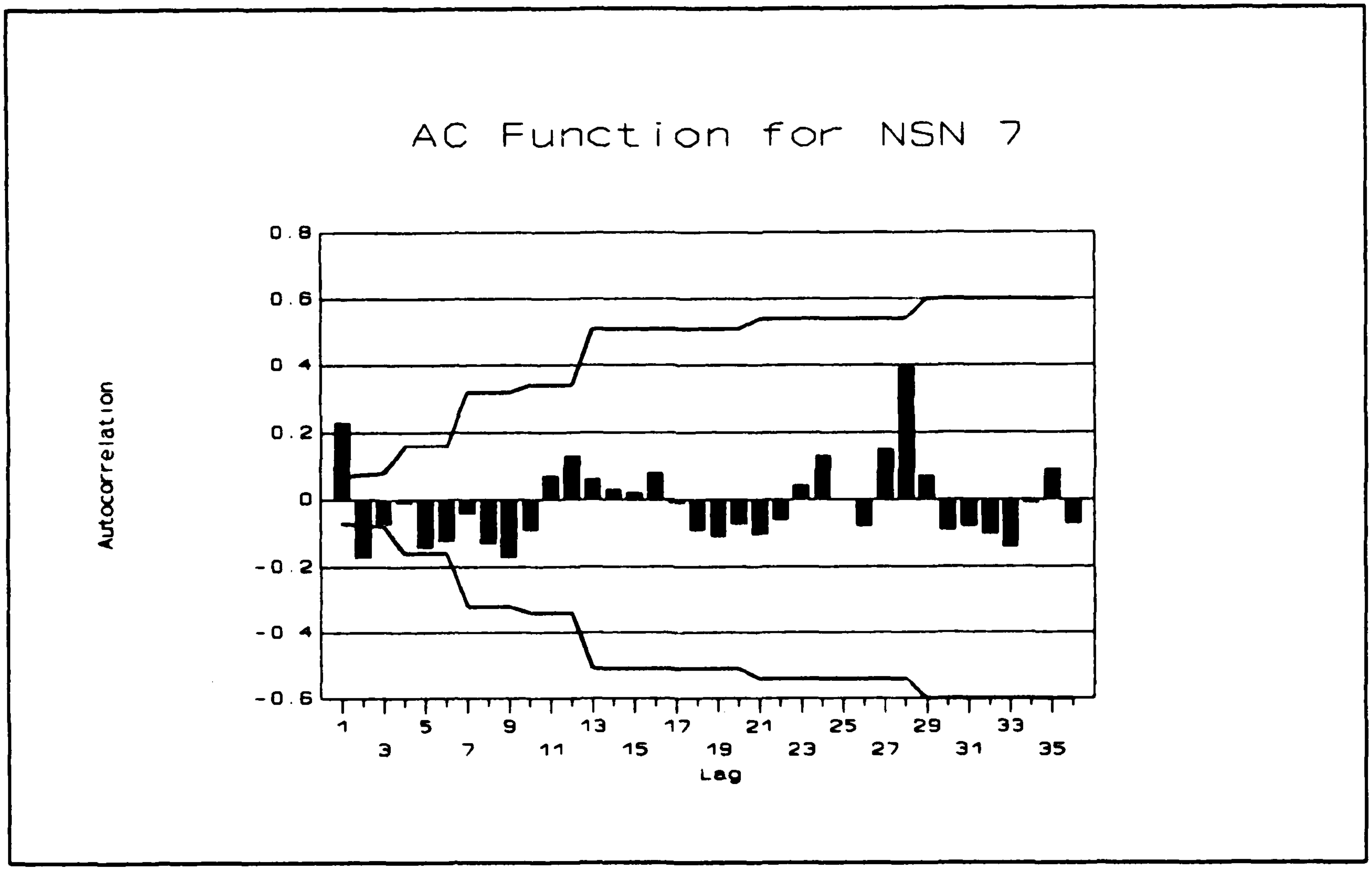

Figure 38. Autocorrelation Function for NSN 7

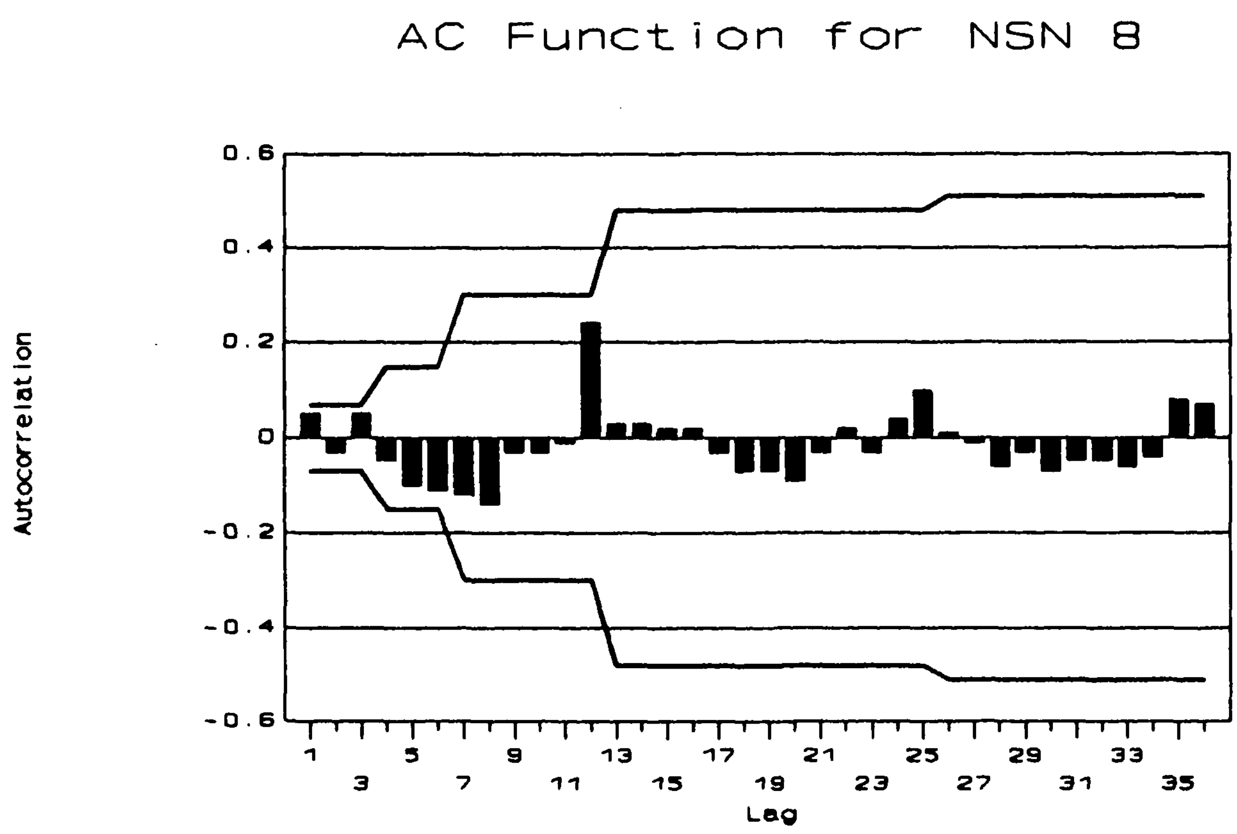

Figure 39. Autocorrelation Function for NSN 8

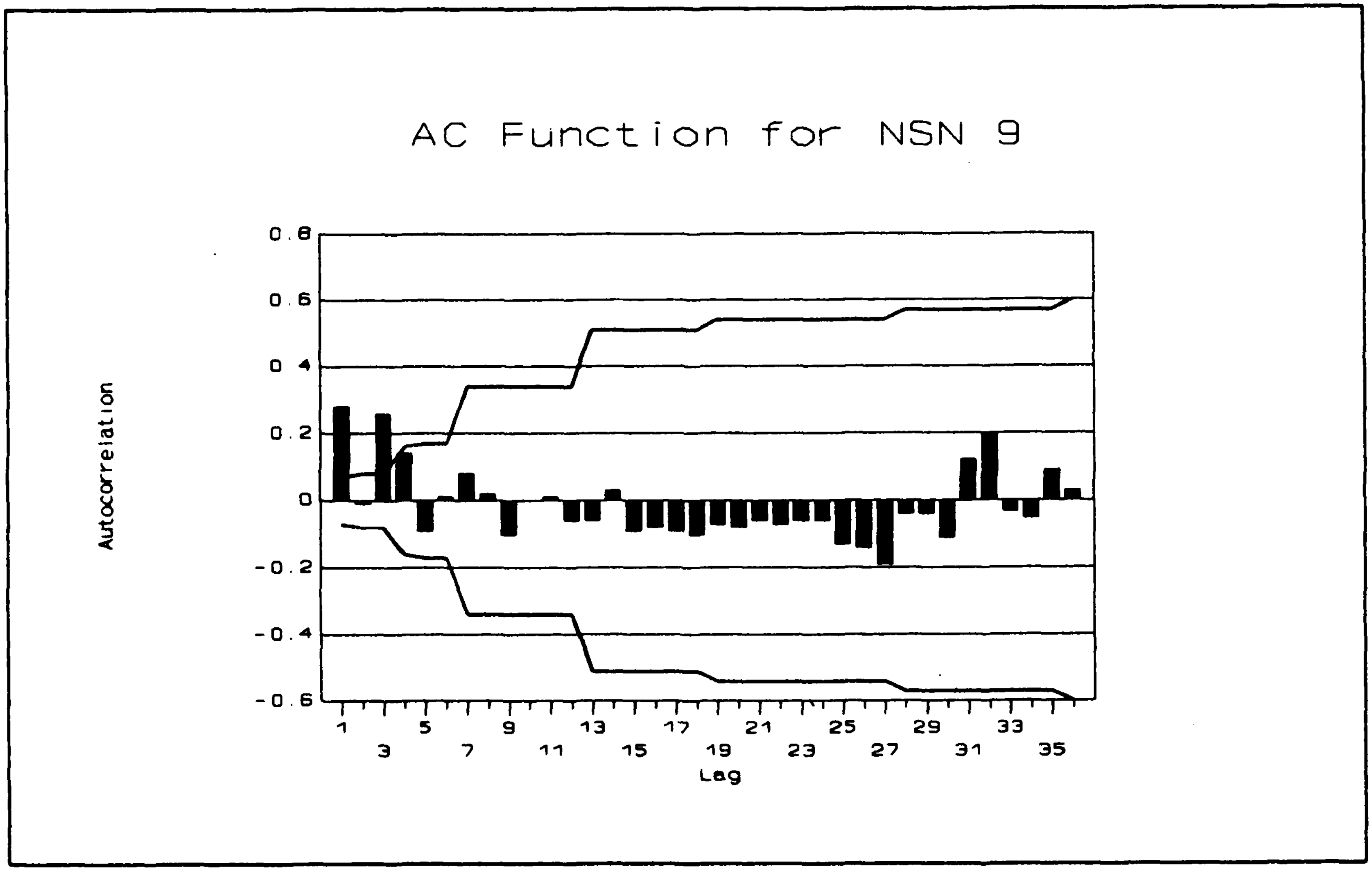

Figure 40. Autocorrelation Function for NSN 9

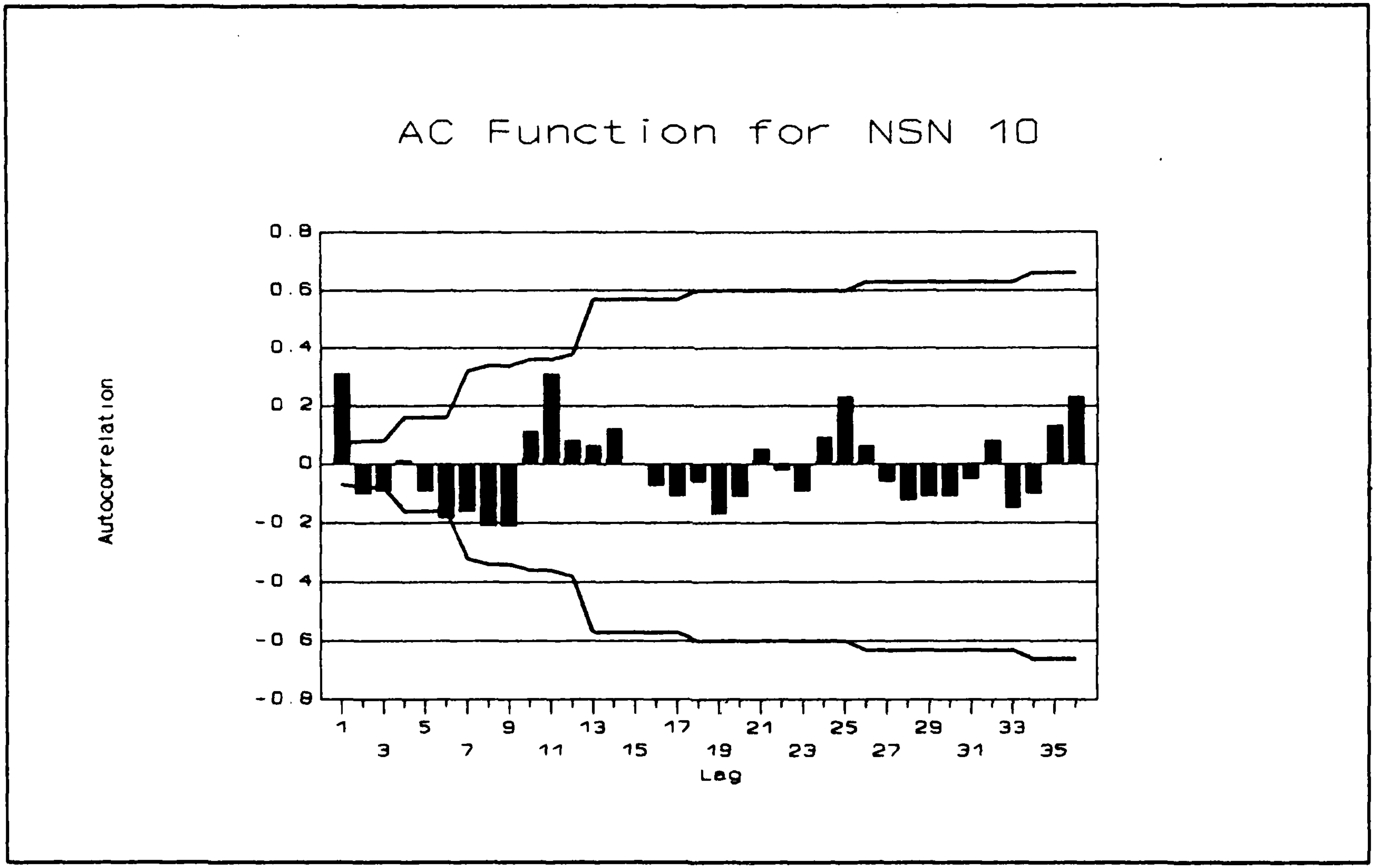

Figure 41. Autocorrelation Function for NSN 10

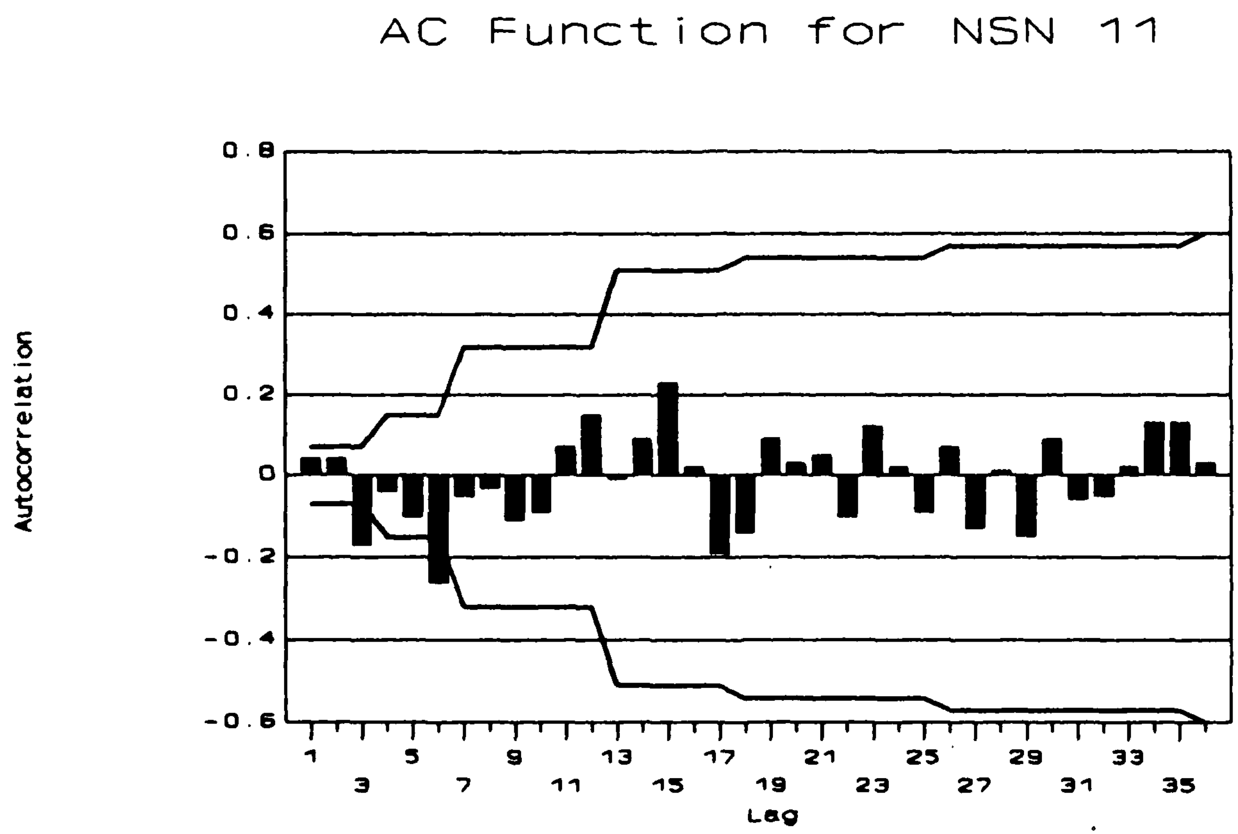

Figure 42. Autocorrelation Function for NSN 11

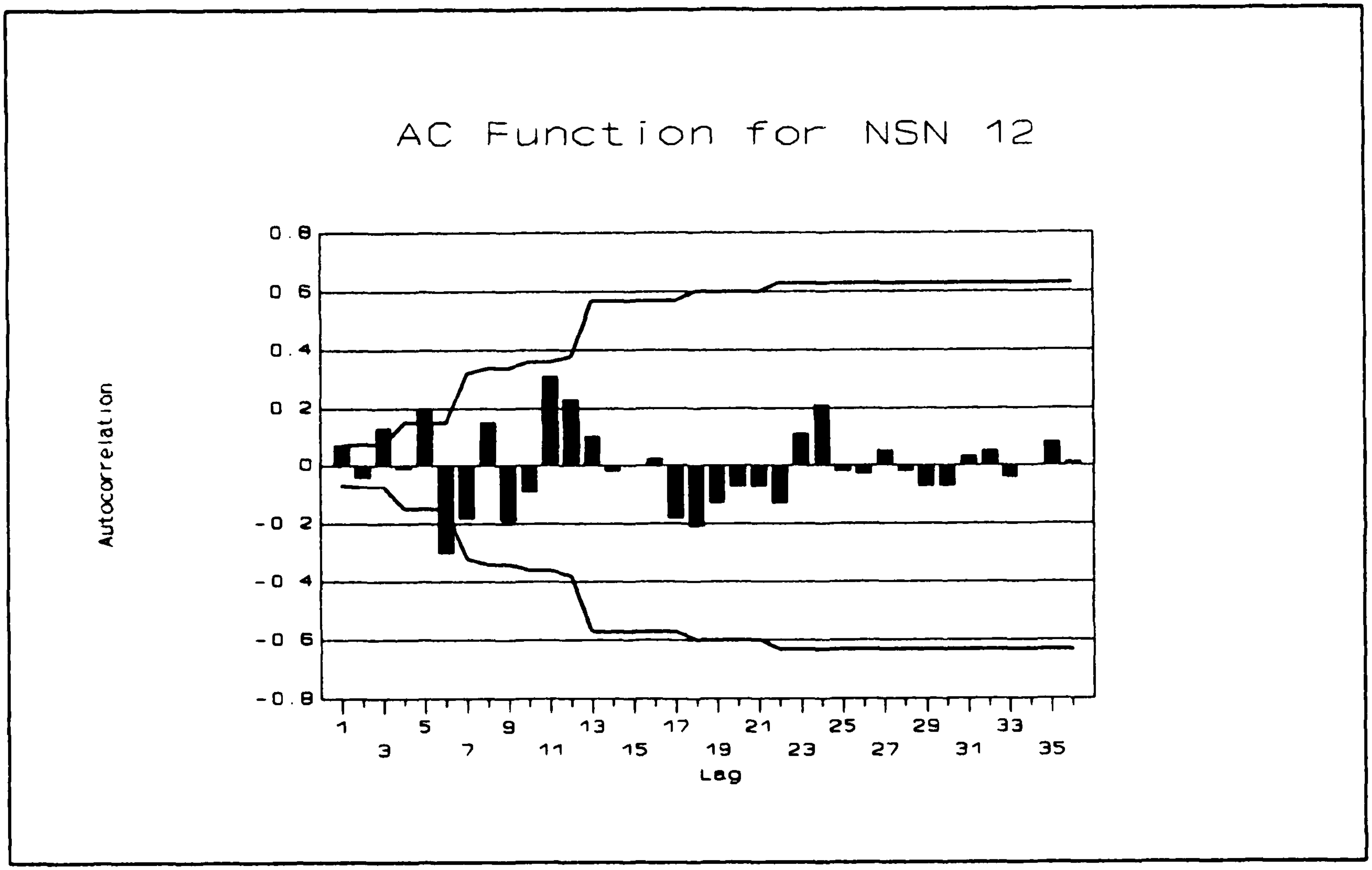

Figure 43. Autocorrelation Function for NSN 12

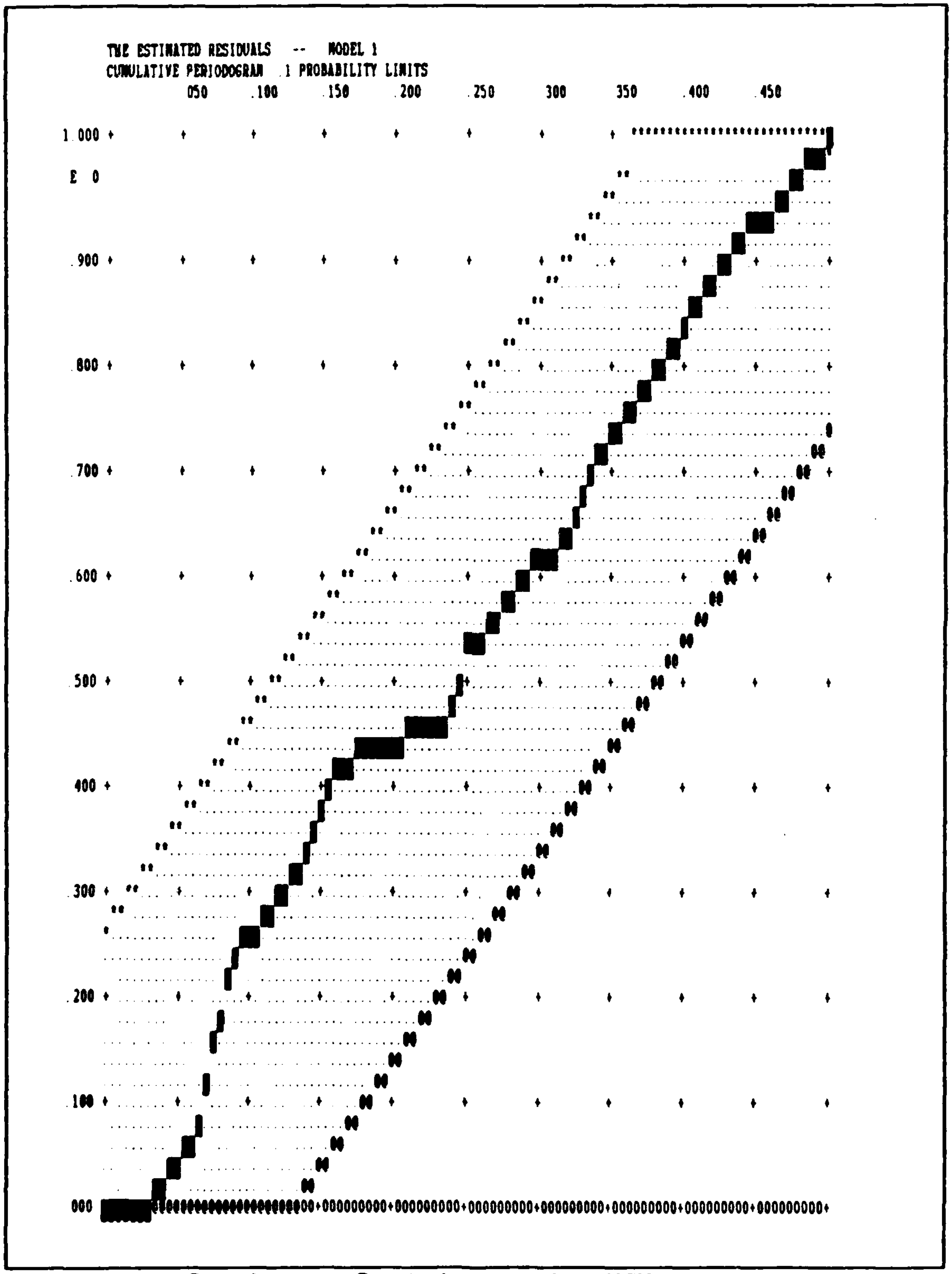

Figure 44. Cumulative Periodogram for NSN 1

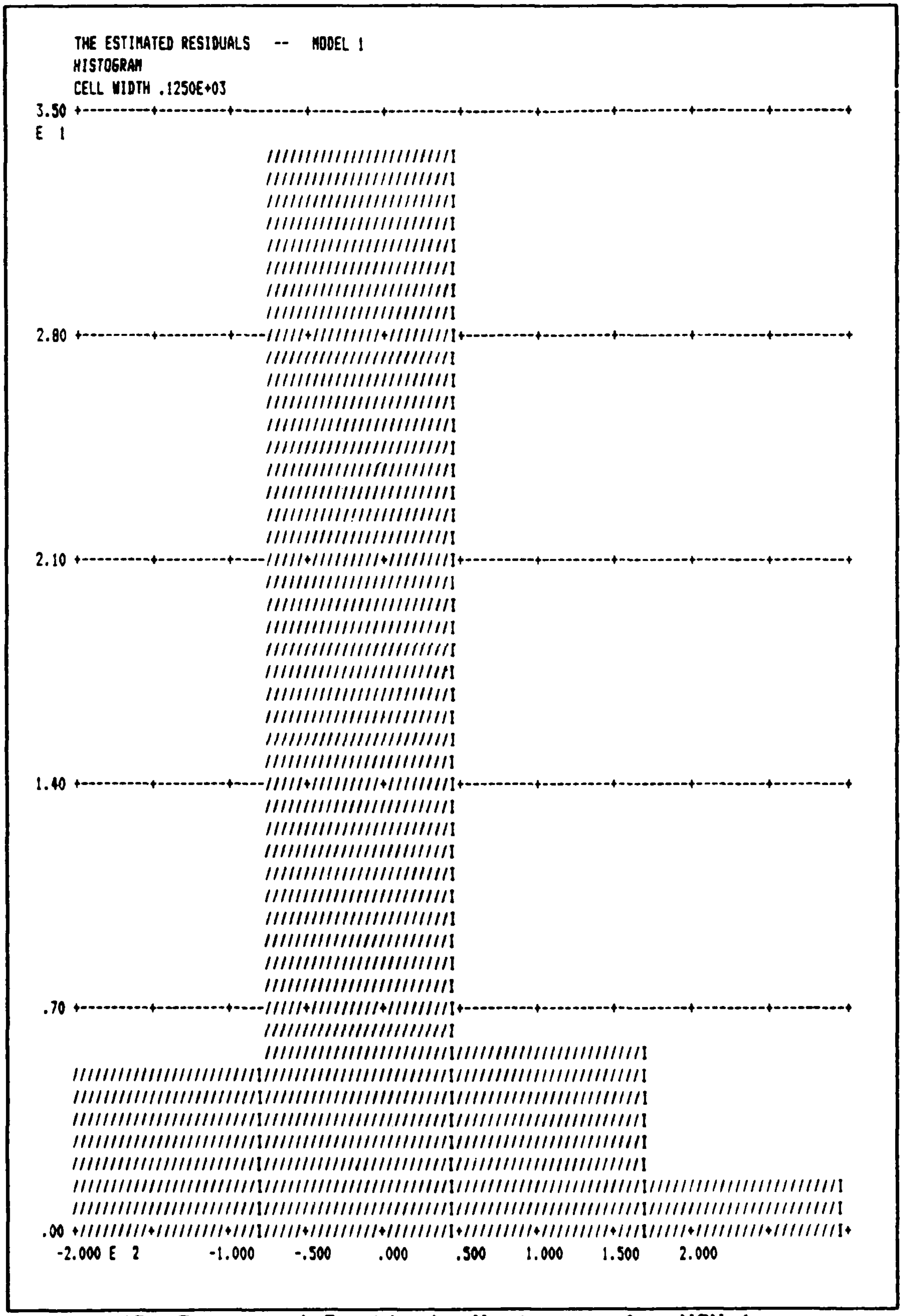

Figure 45. Estimated Residuals Histogram for NSN 1

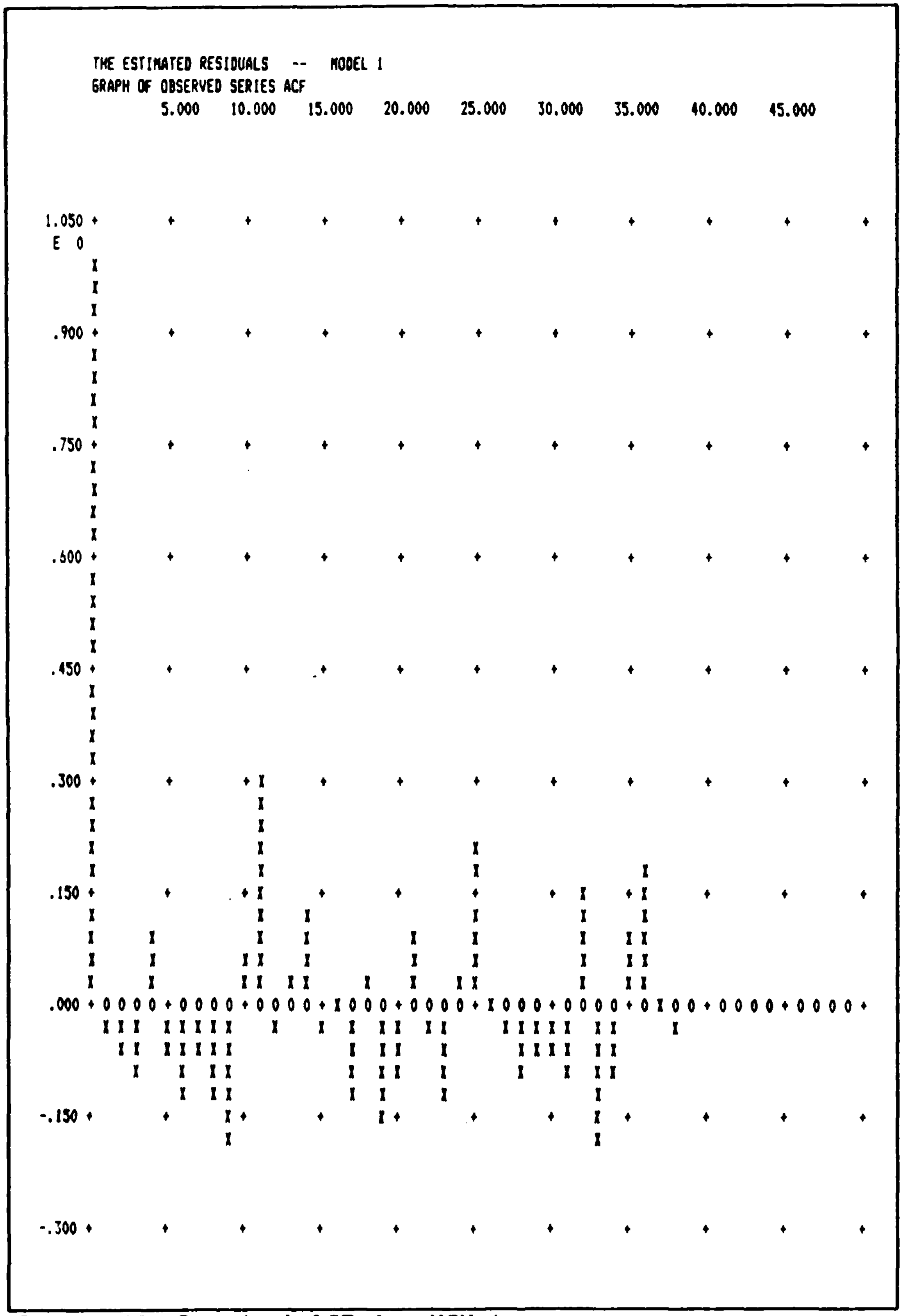

Figure 46. Residual ACF for NSN 1

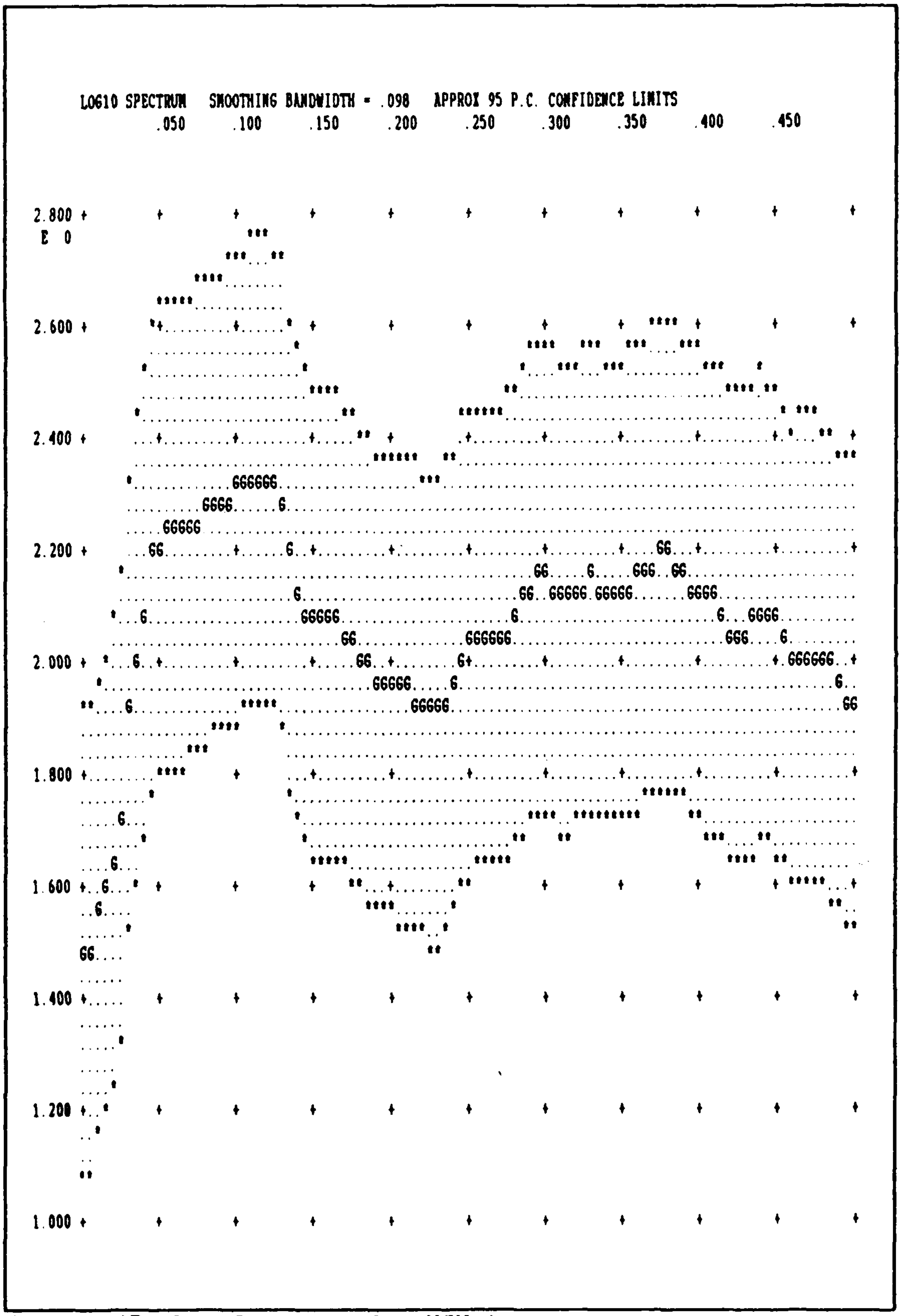

Figure 47. Log Spectrum for NSN 1

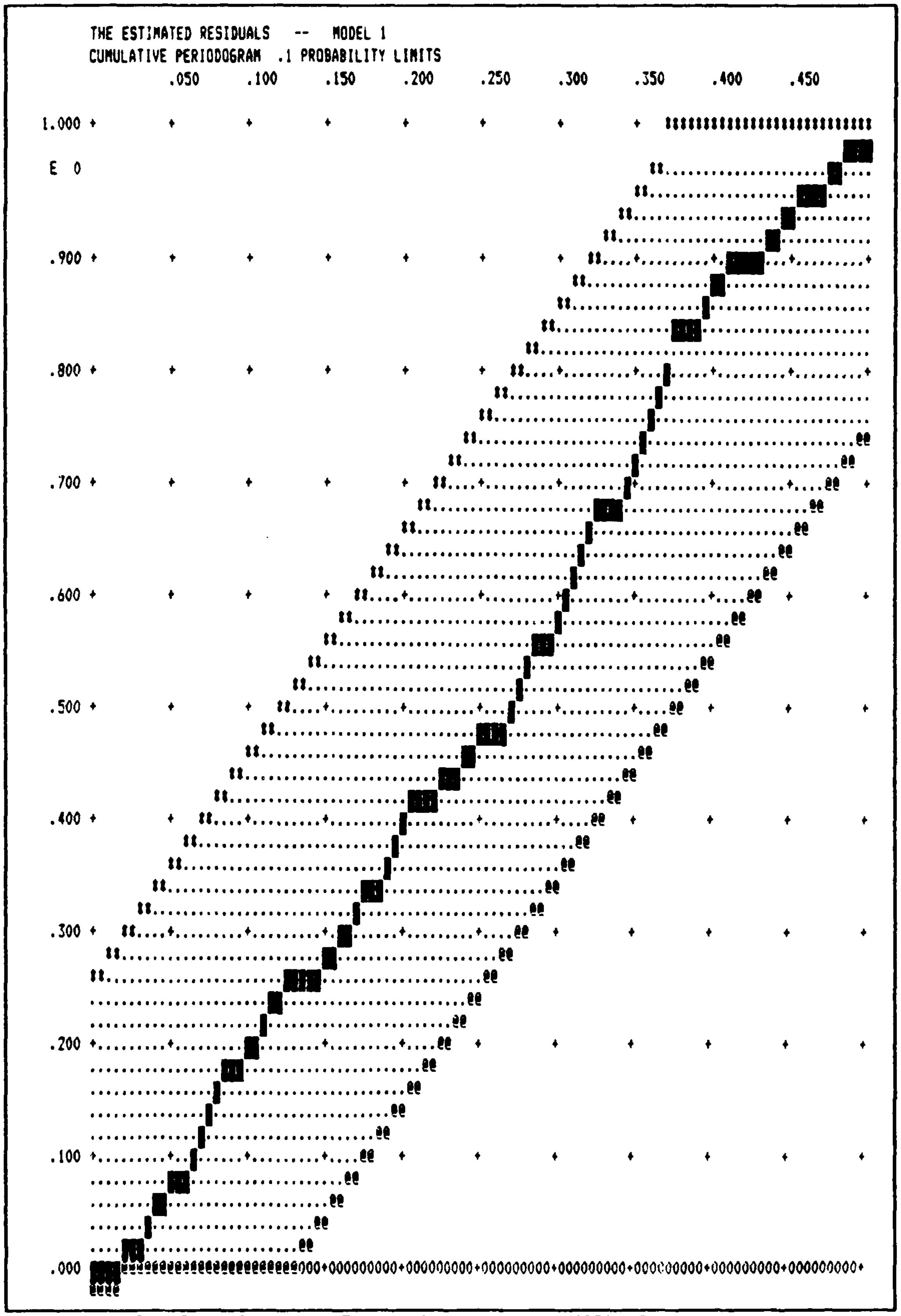

Figure 48. Cumulative Periodogram for NSN 3

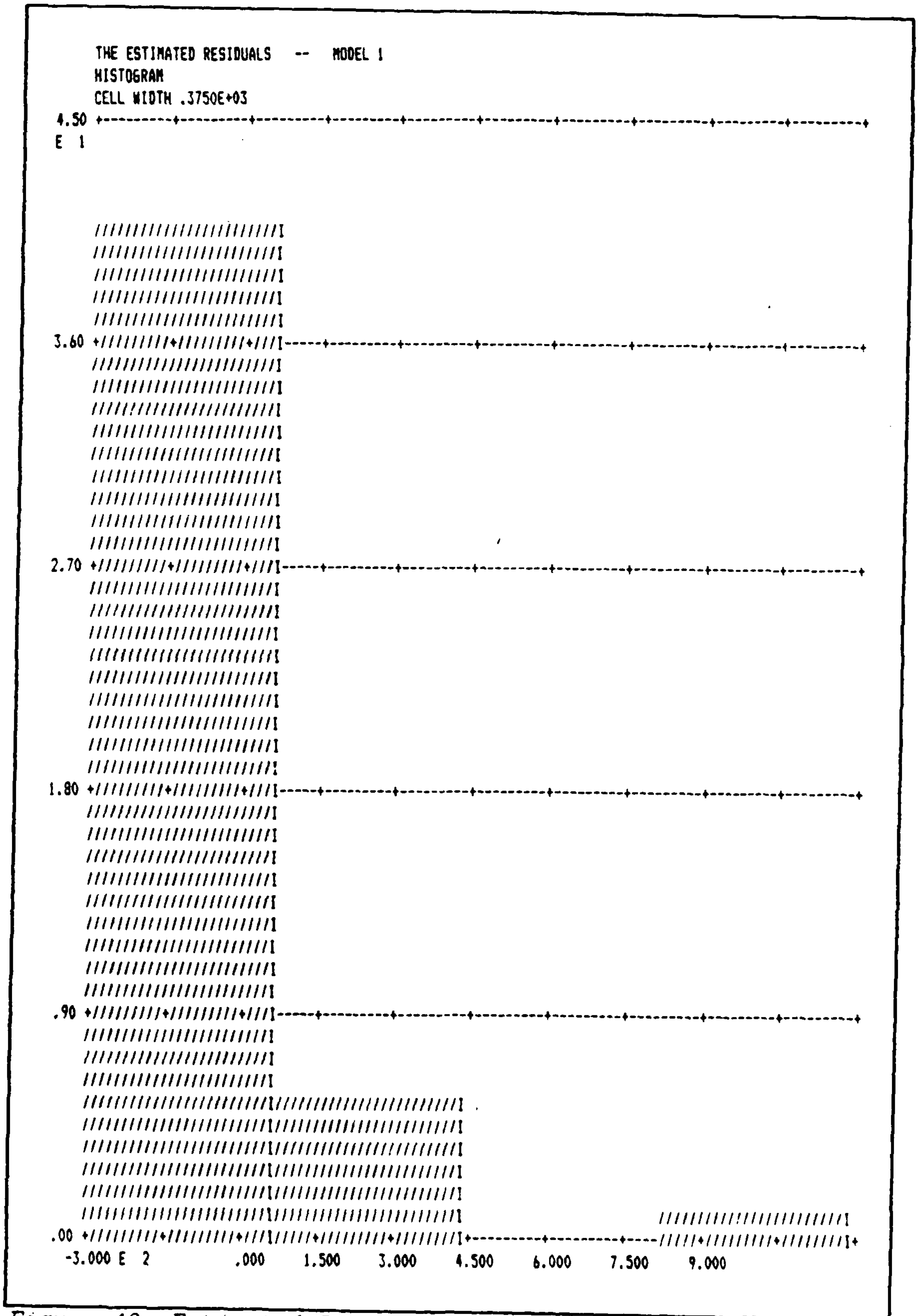

Figure 49. Estimated Residuals Histogram for NSN 3

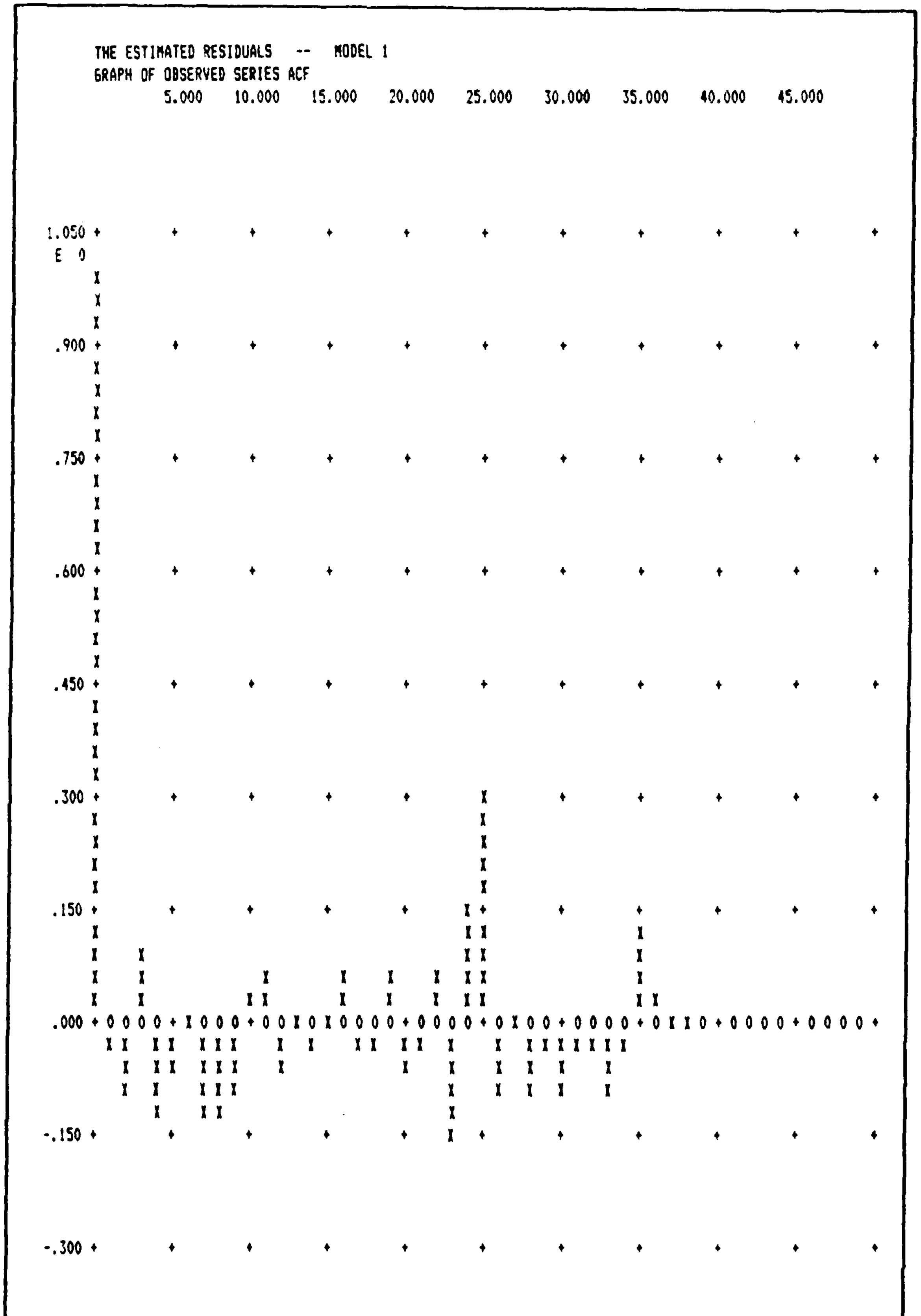

Figure 50. Residual ACF for NSN 3

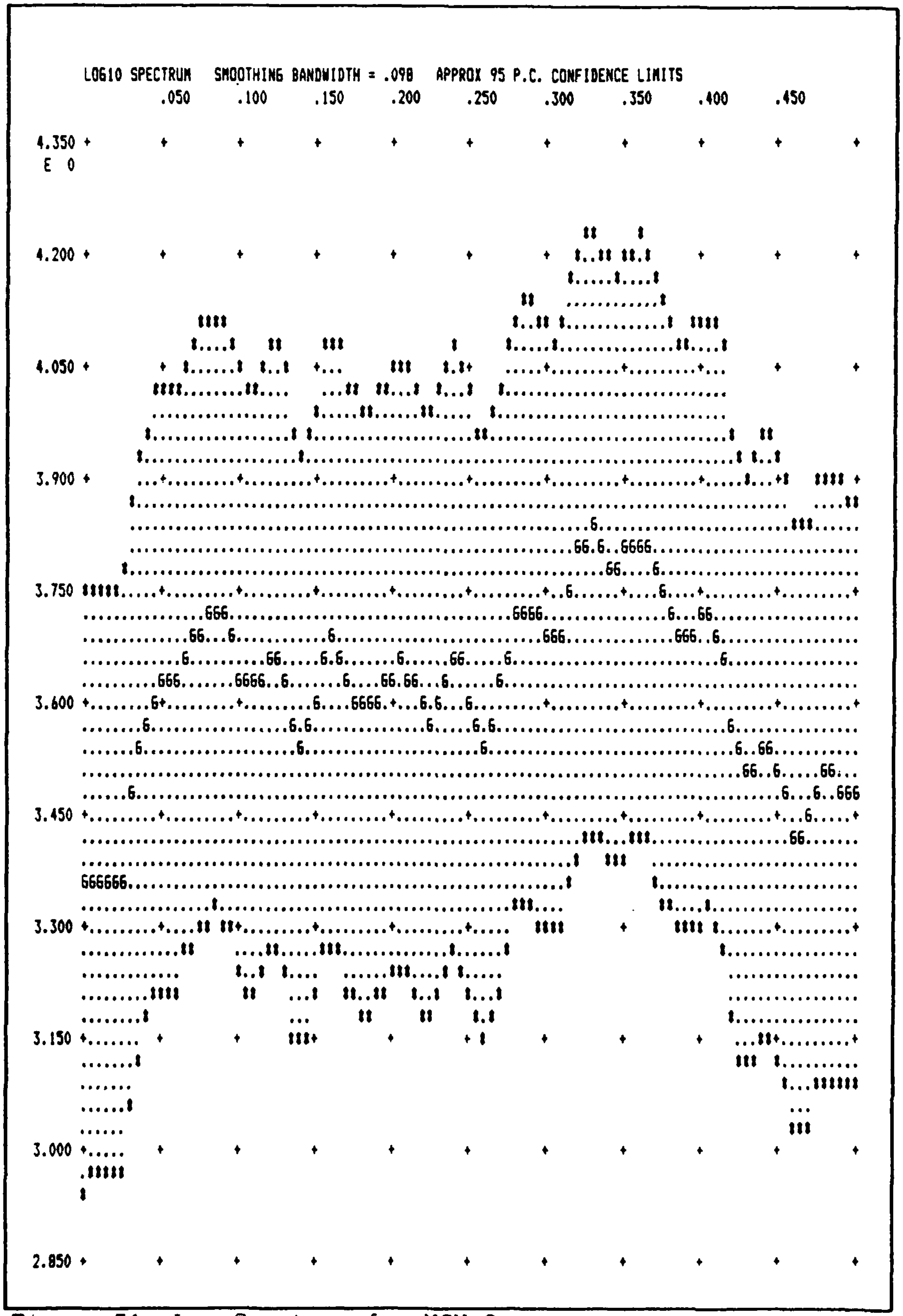

Figure 51. Log Spectrum for NSN 3

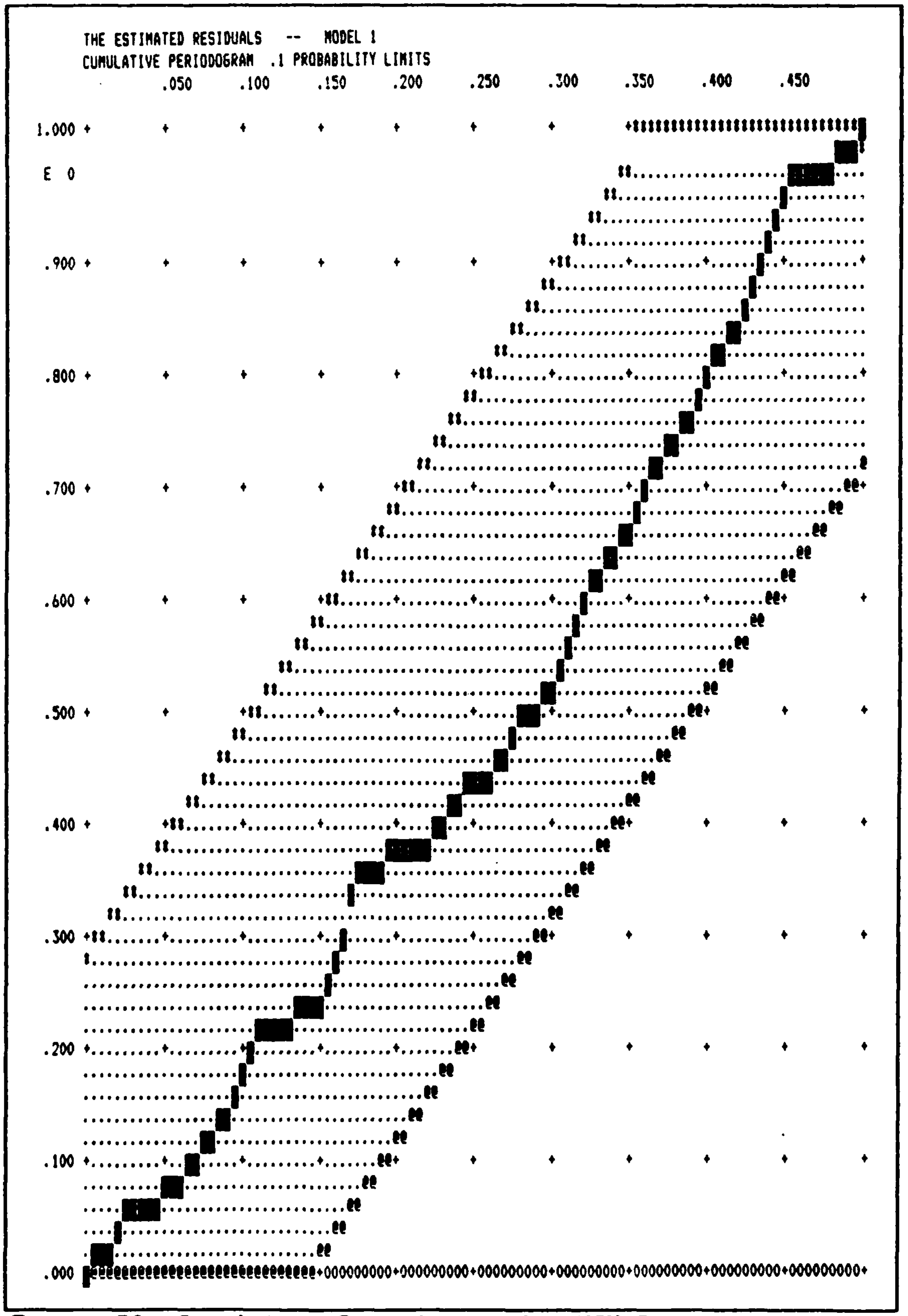

Figure 52. Cumulative Periodogram for NSN 5

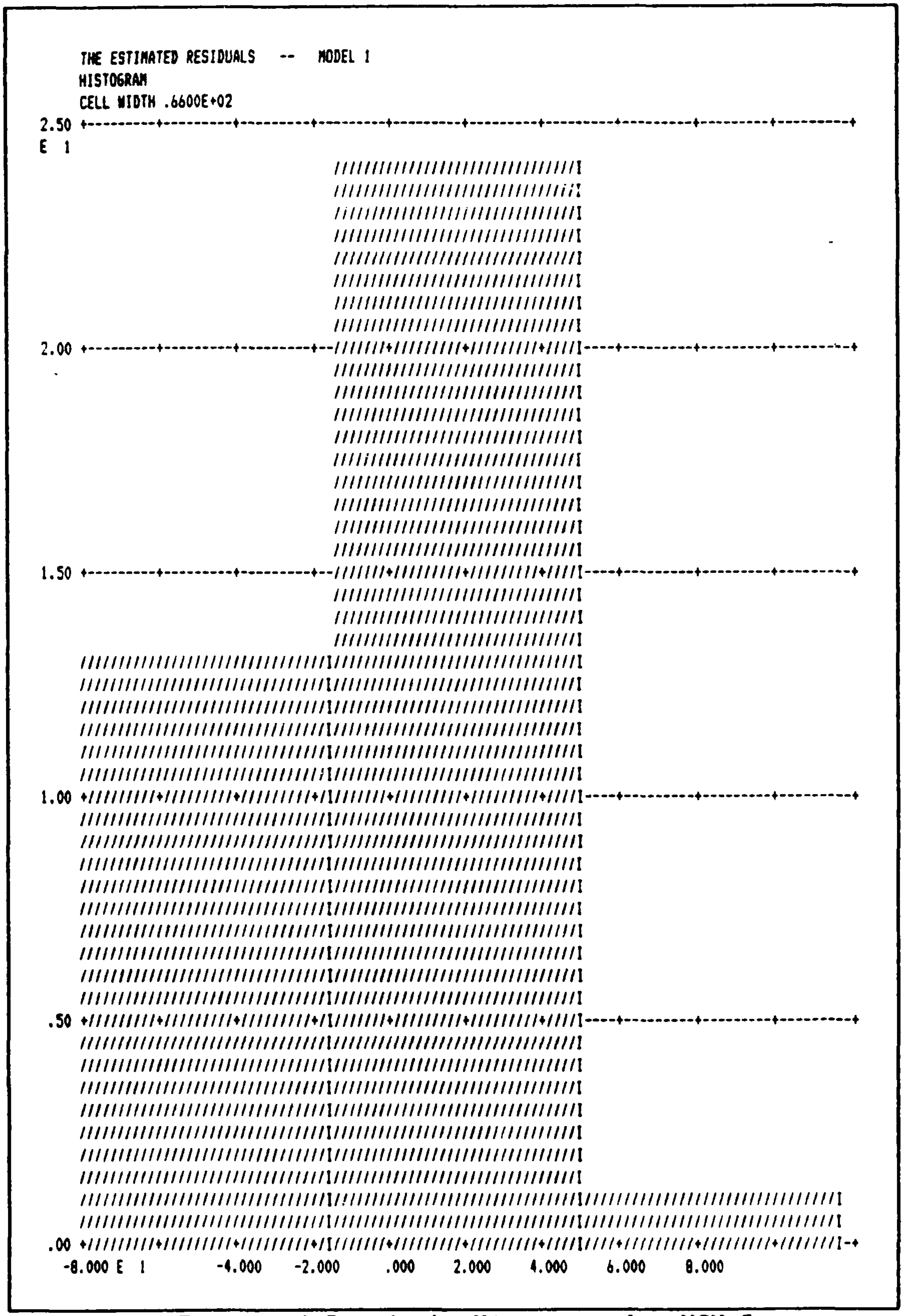

Figure 53. Estimated Residuals Histogram for NSN 5

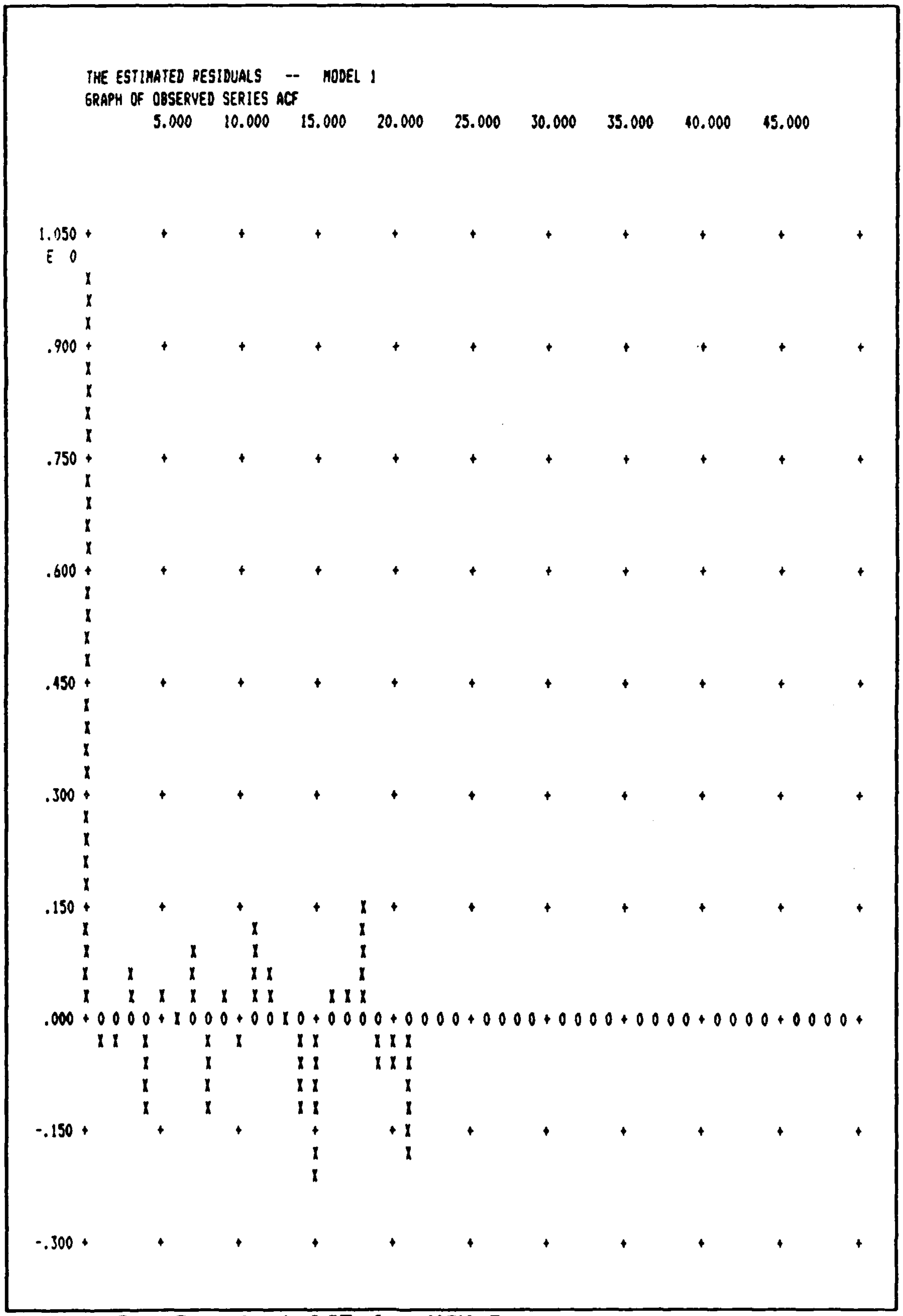

Figure 54. Residual ACF for NSN 5

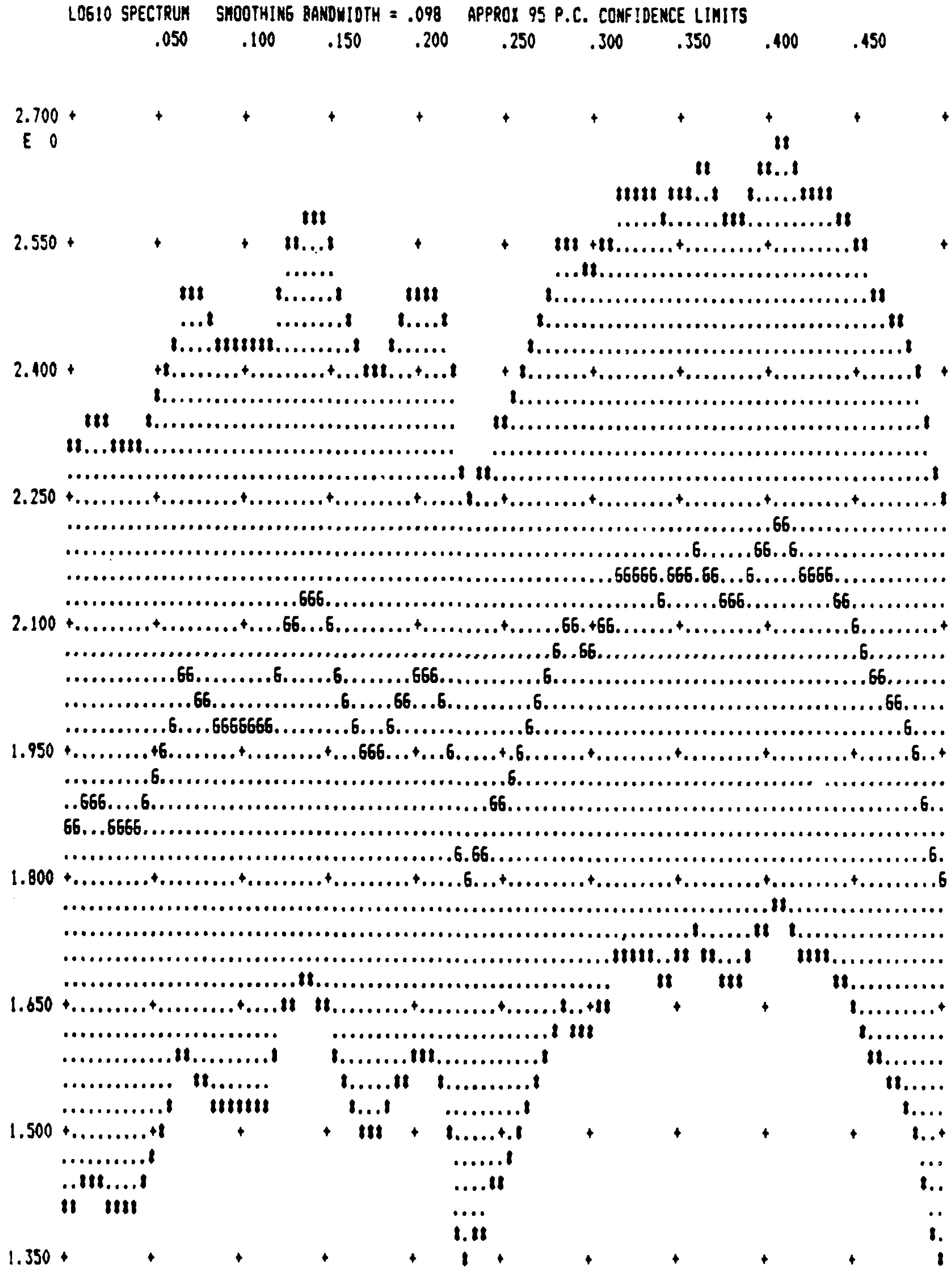

Figure 55. Log Spectrum for NSN 5

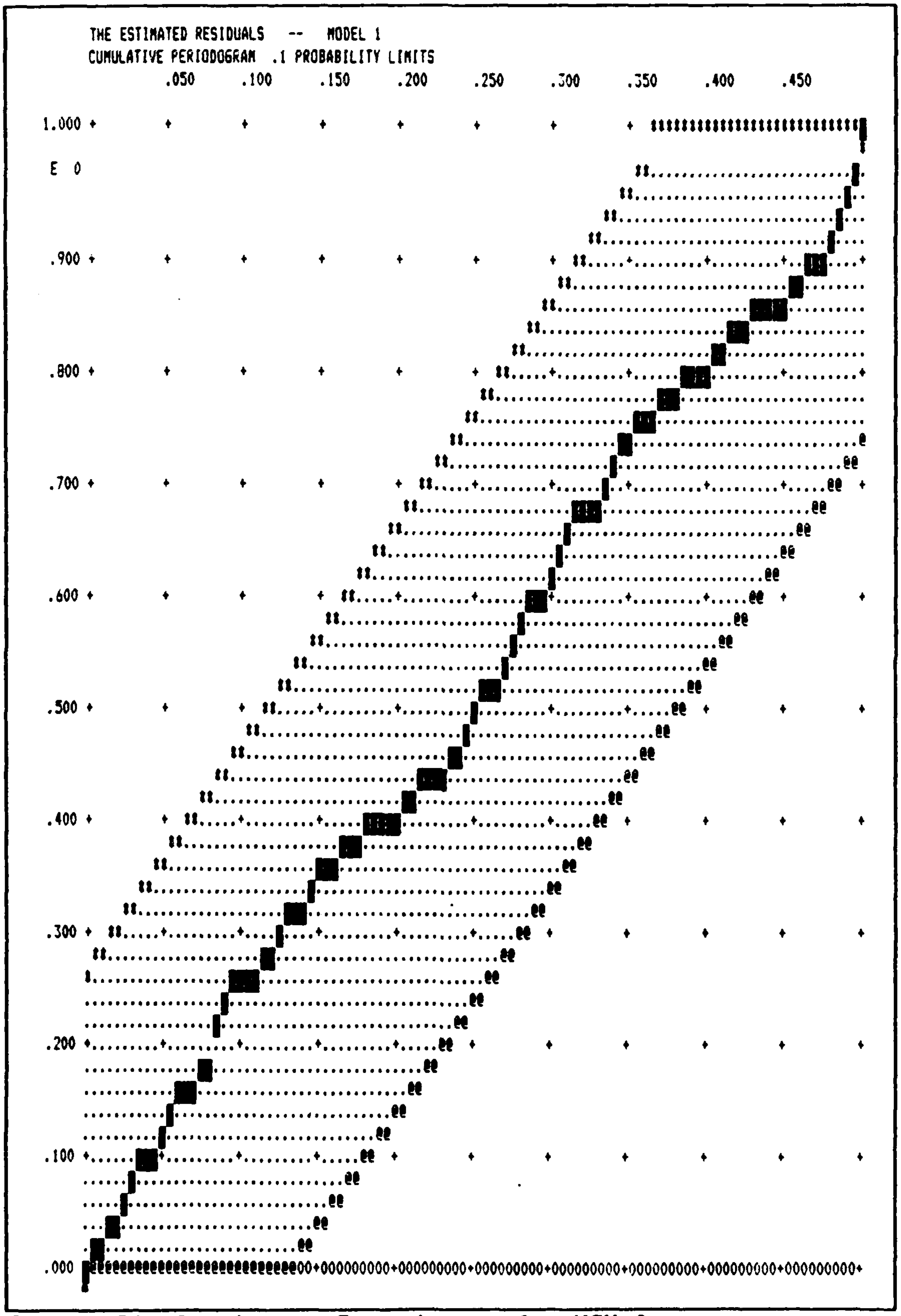

Figure 56. Cumulative Periodogram for NSN 9

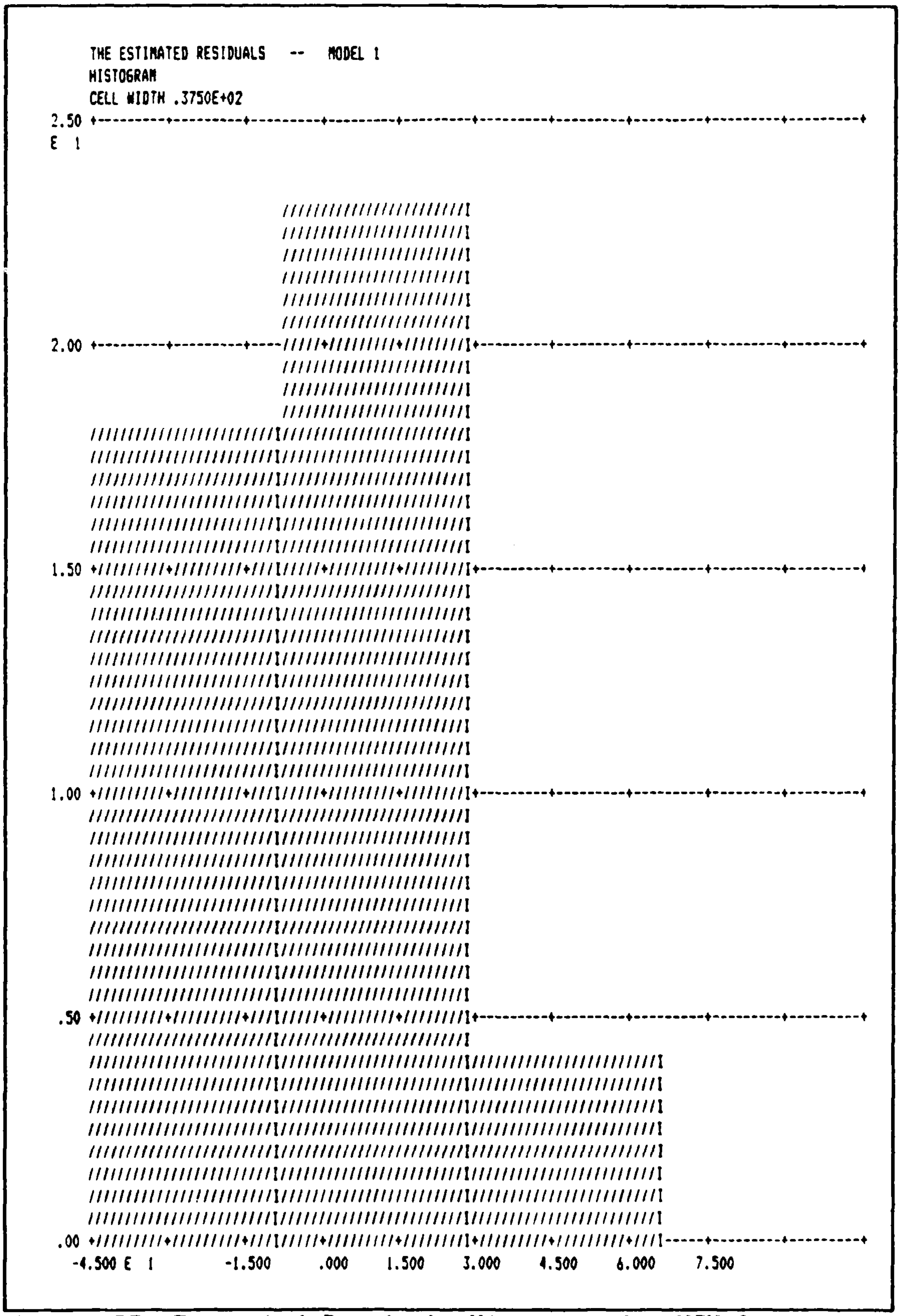

Figure 57. Estimated Residuals Histogram for NSN 9

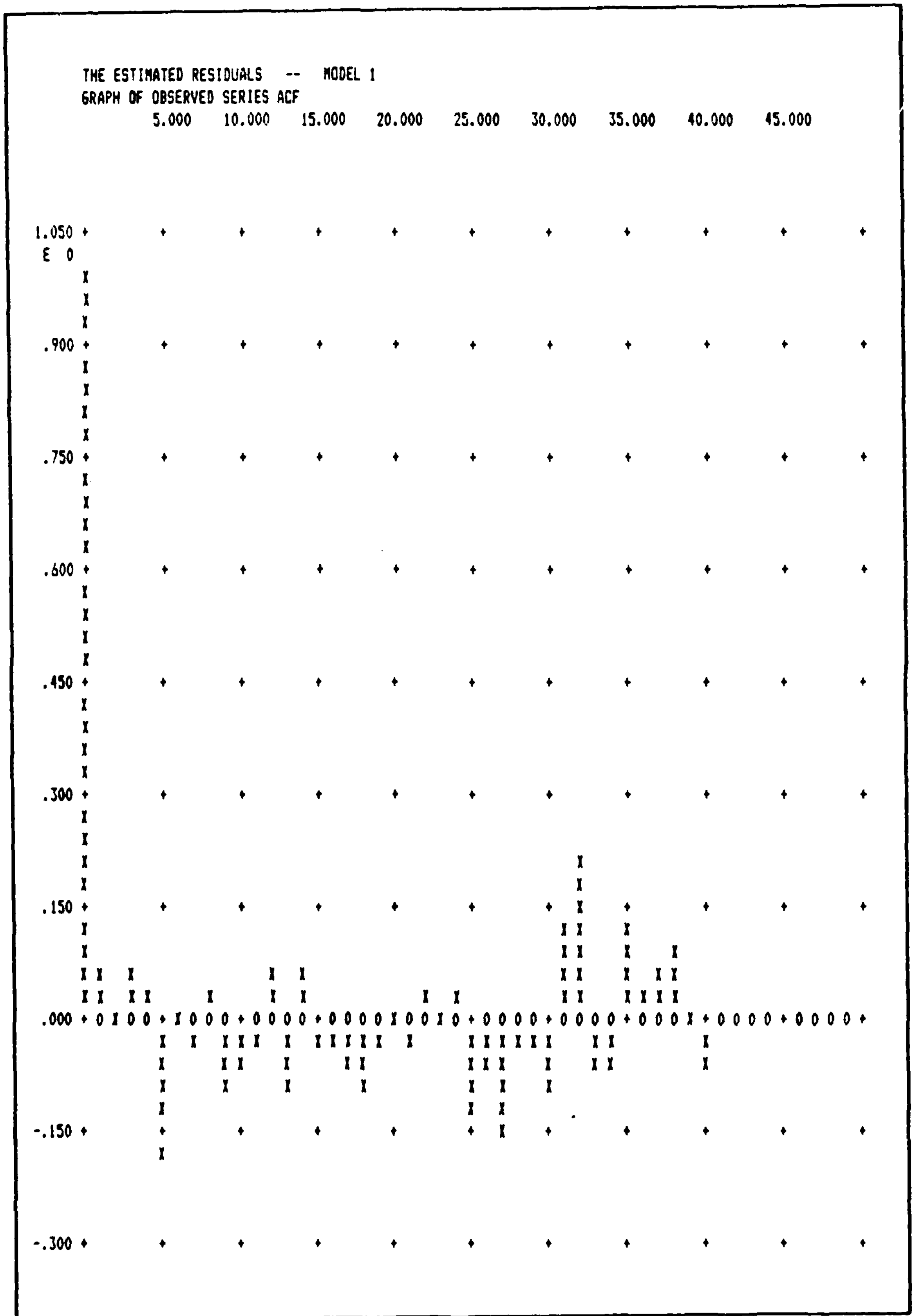

Figure 58. Residual ACF for NSN 9

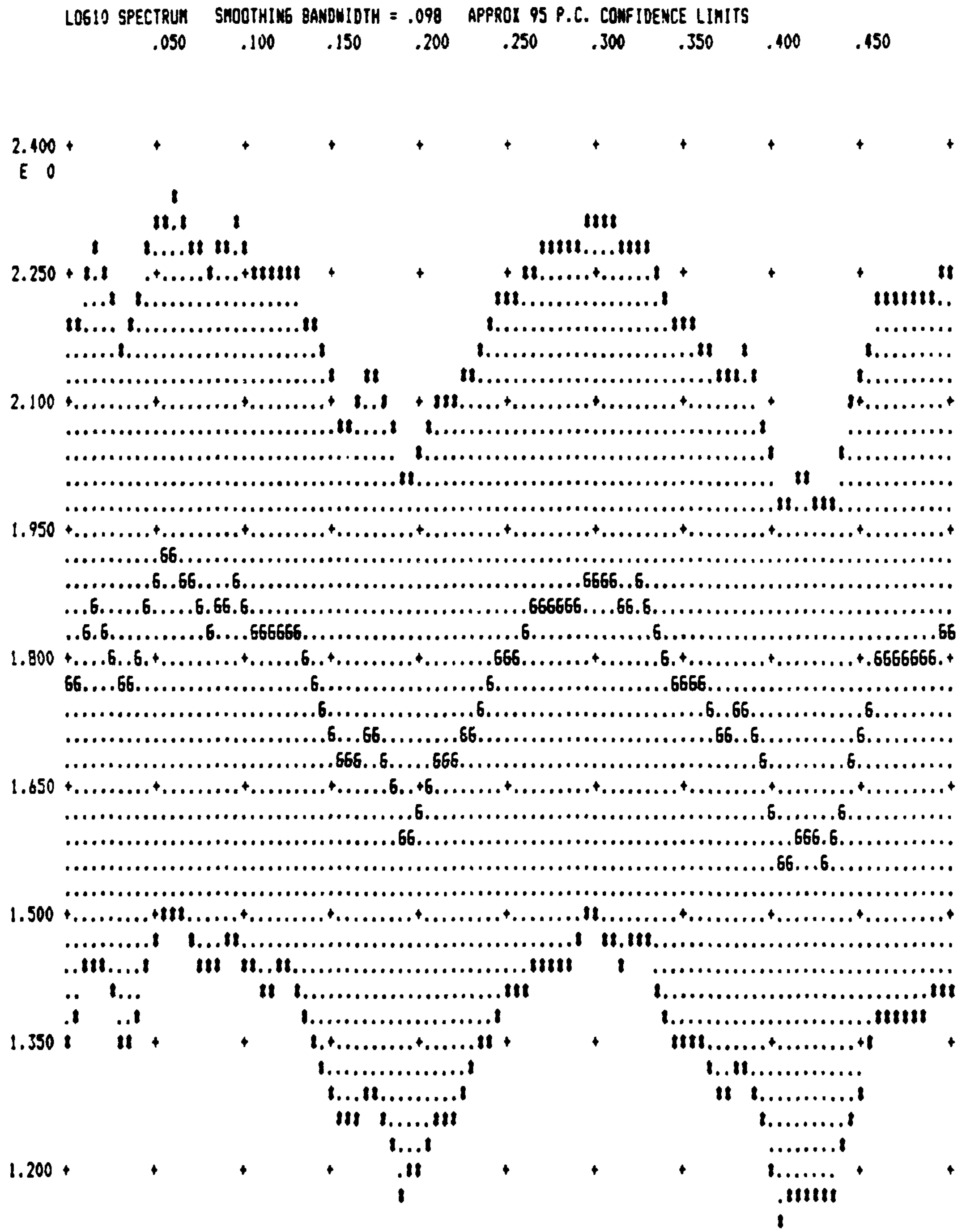

Figure 59. Log Spectrum for NSN 9

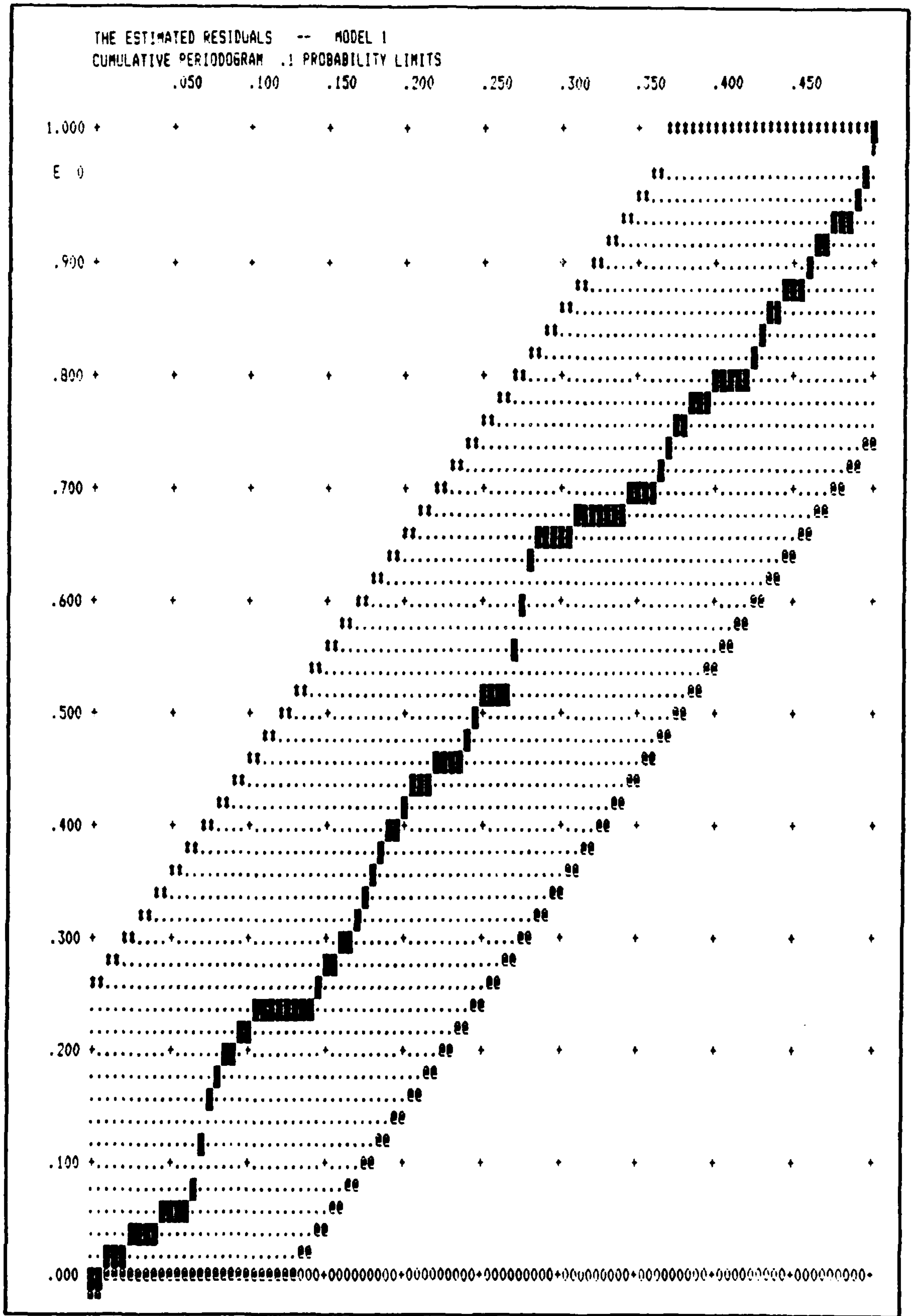

Figure 60. Cumulative Periodogram for NSN 10

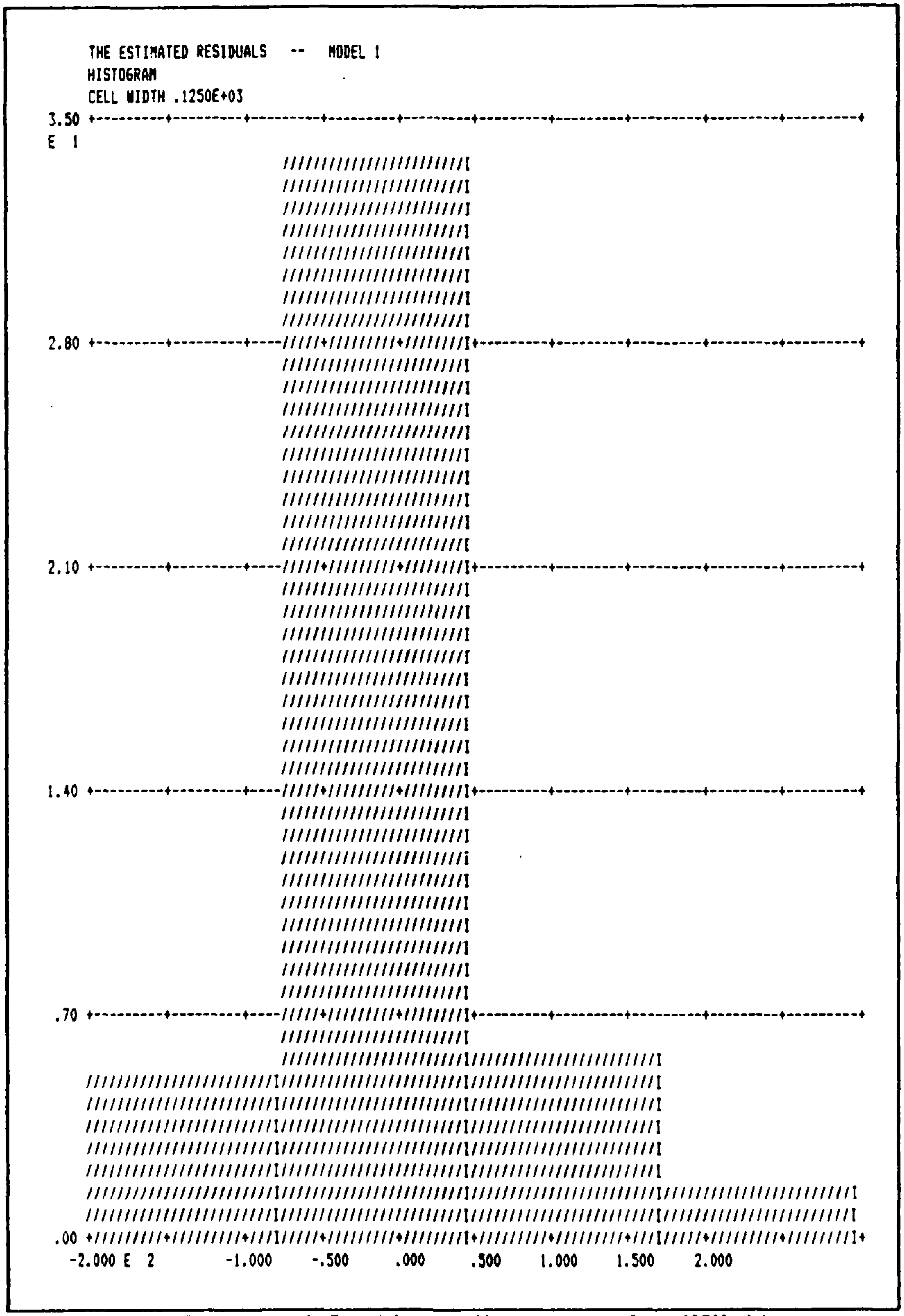

Figure 61. Estimated Residuals Histogram for NSN 10

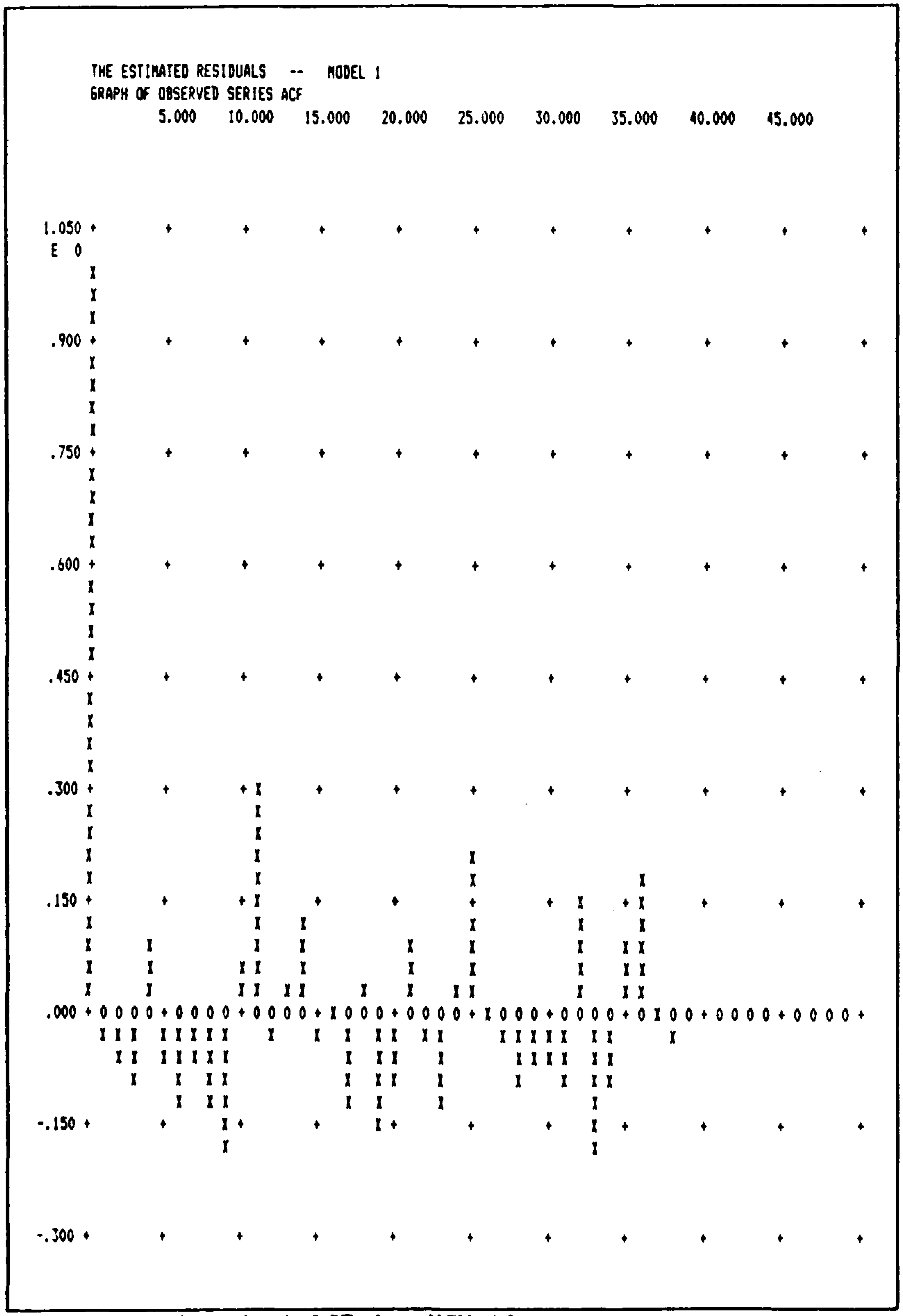

Figure 62. Residual ACF for NSN 10

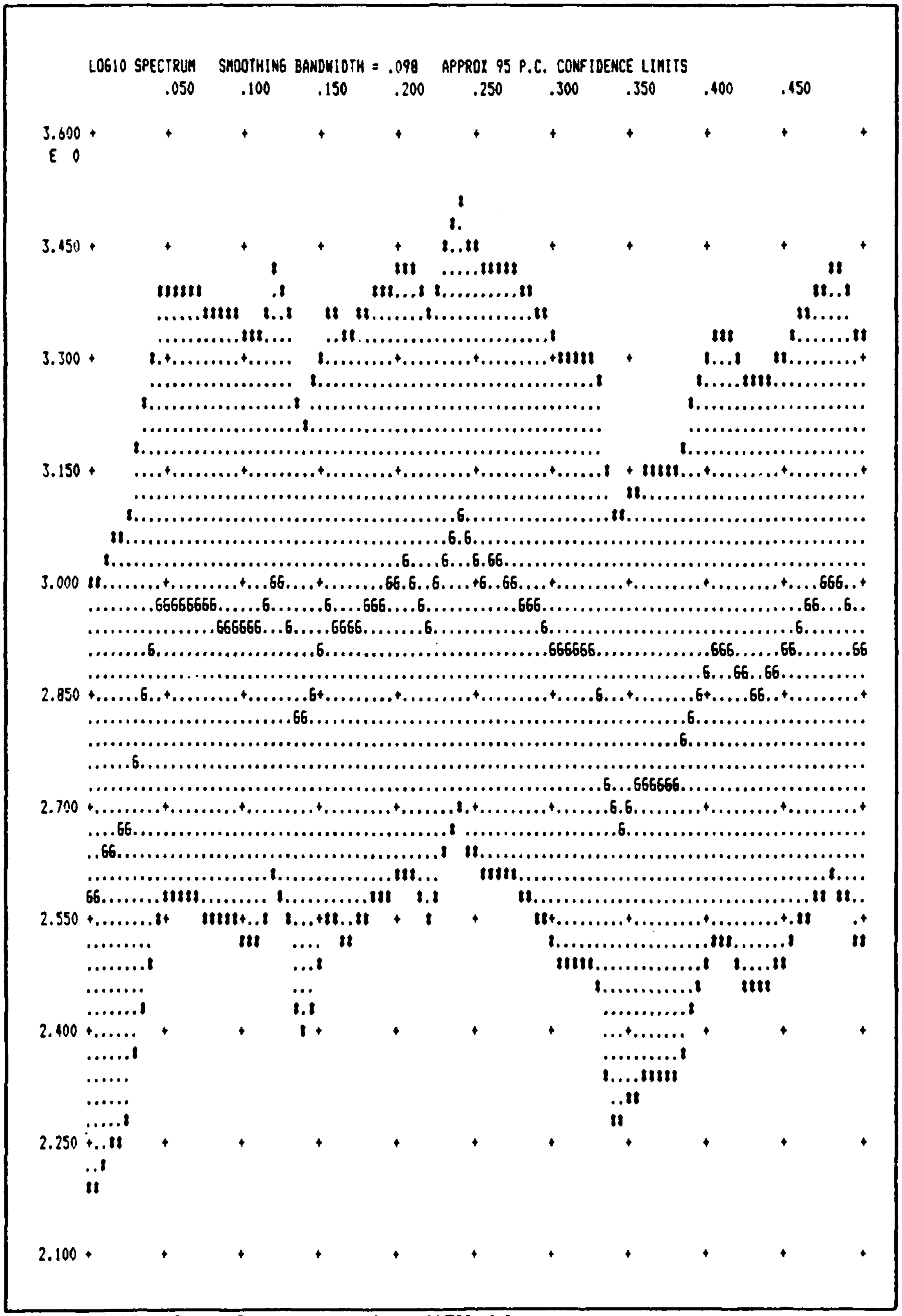

Figure 63. Log Spectrum for NSN 10

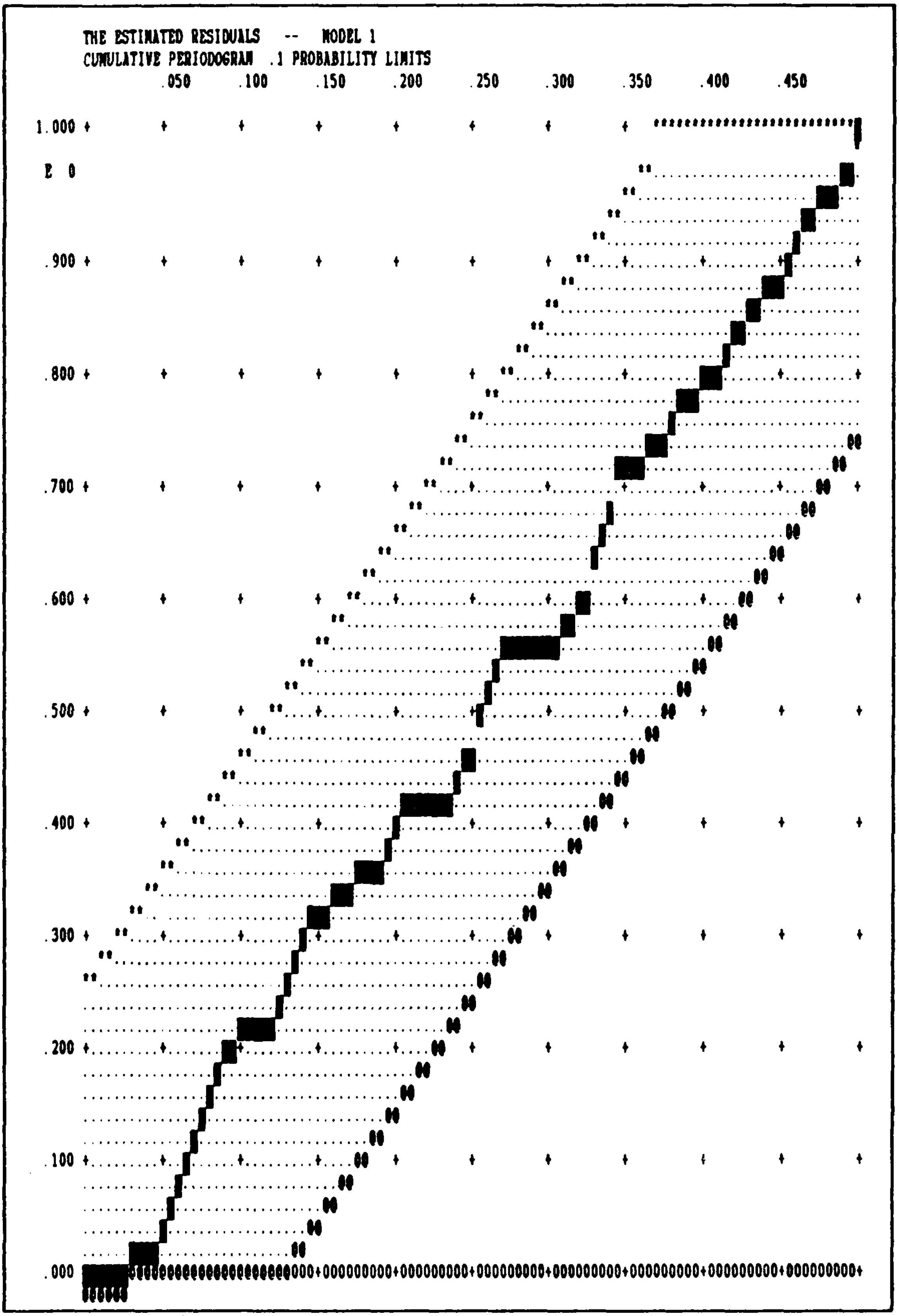

Figure 64. Cumulative Periodogram for NSN 11

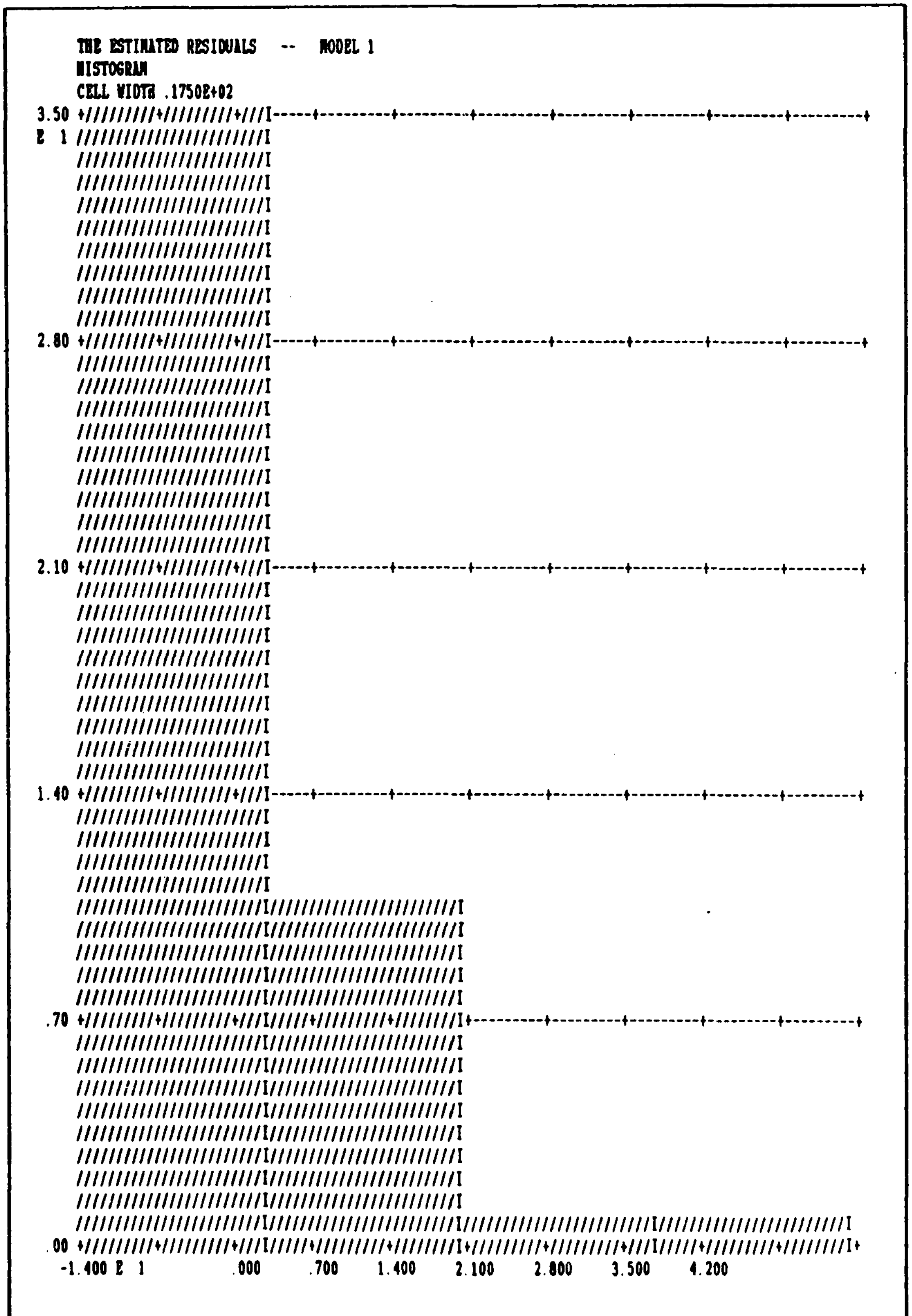

Figure 65. Estimated Residuals Histogram for NSN 11

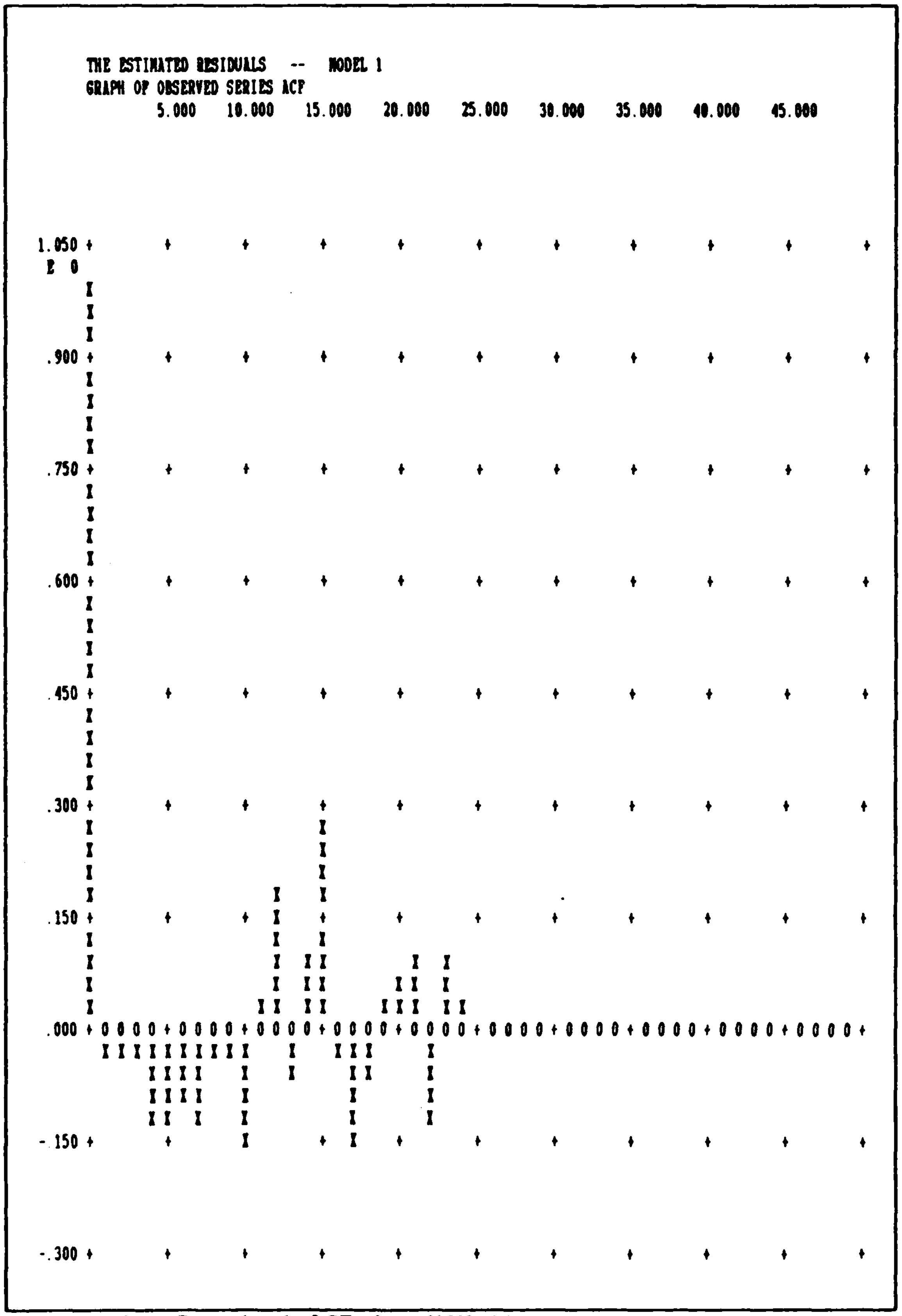

Figure 66. Residual ACF for NSN 11

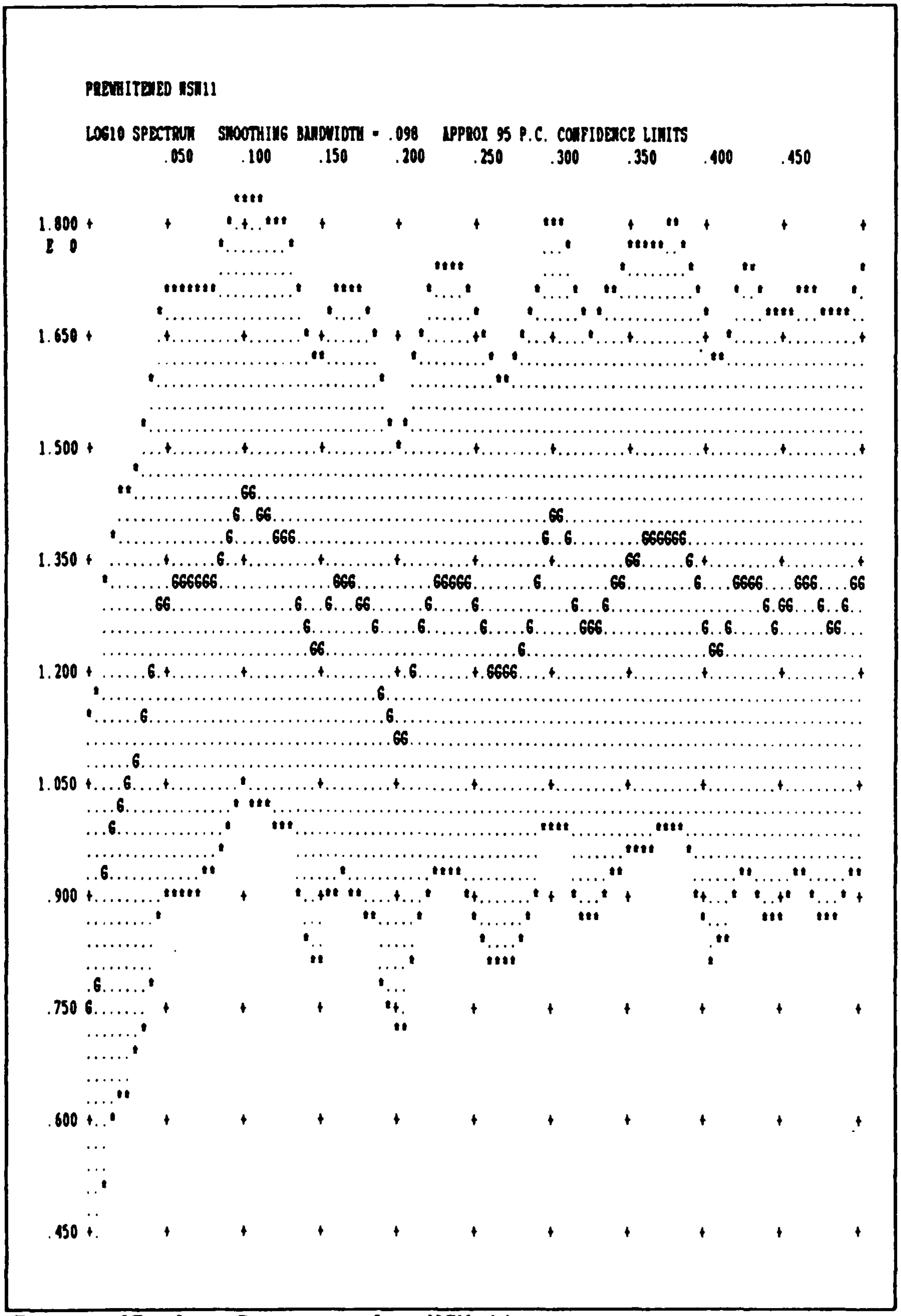

Figure 67. Log Spectrum for NSN 11

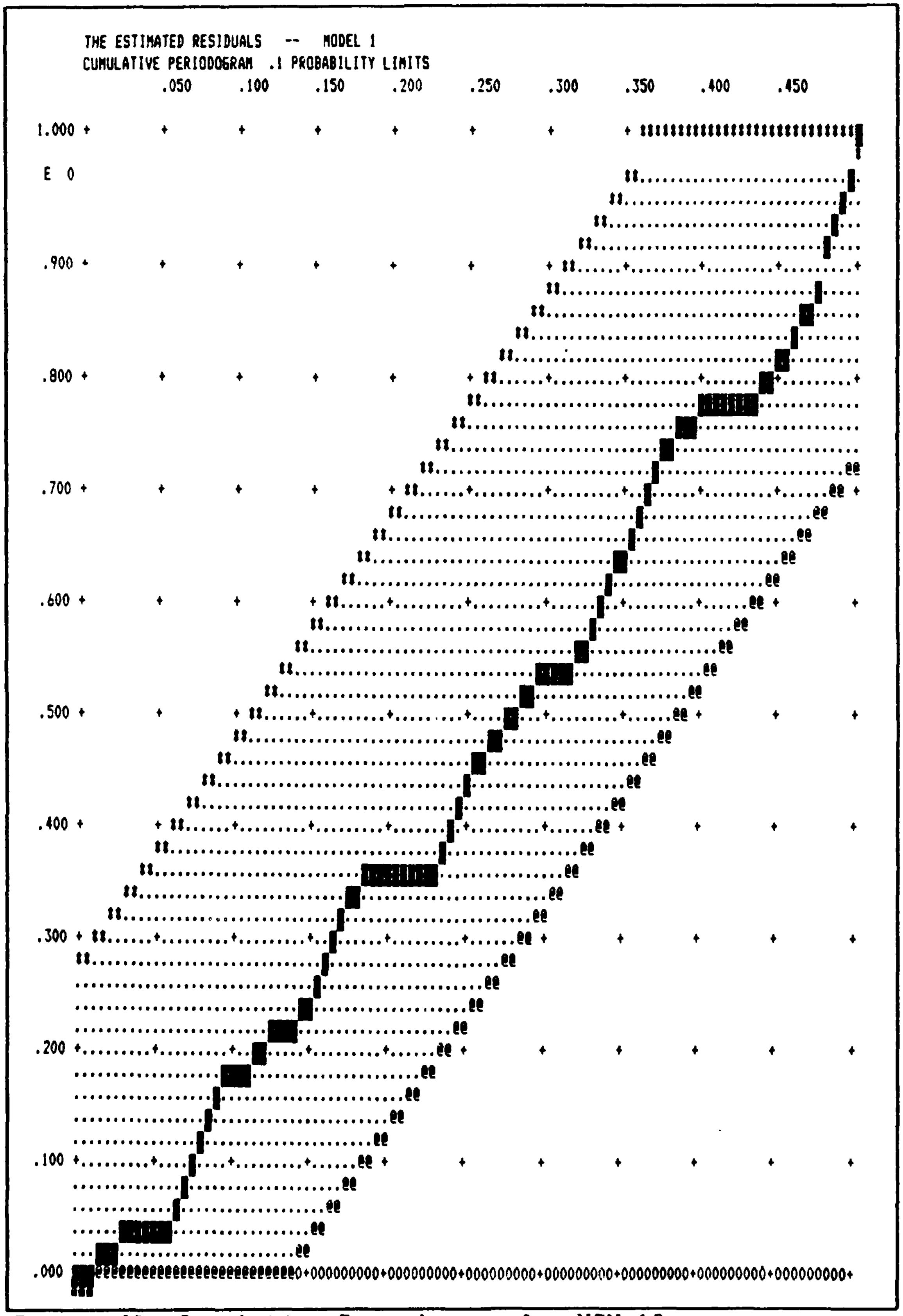

Figure 68. Cumulative Periodogram for NSN 12

THE ESTIMATED RESIDUALS -- MODEL 1
HISTOGRAM
CELL WIDTH .5000E+02

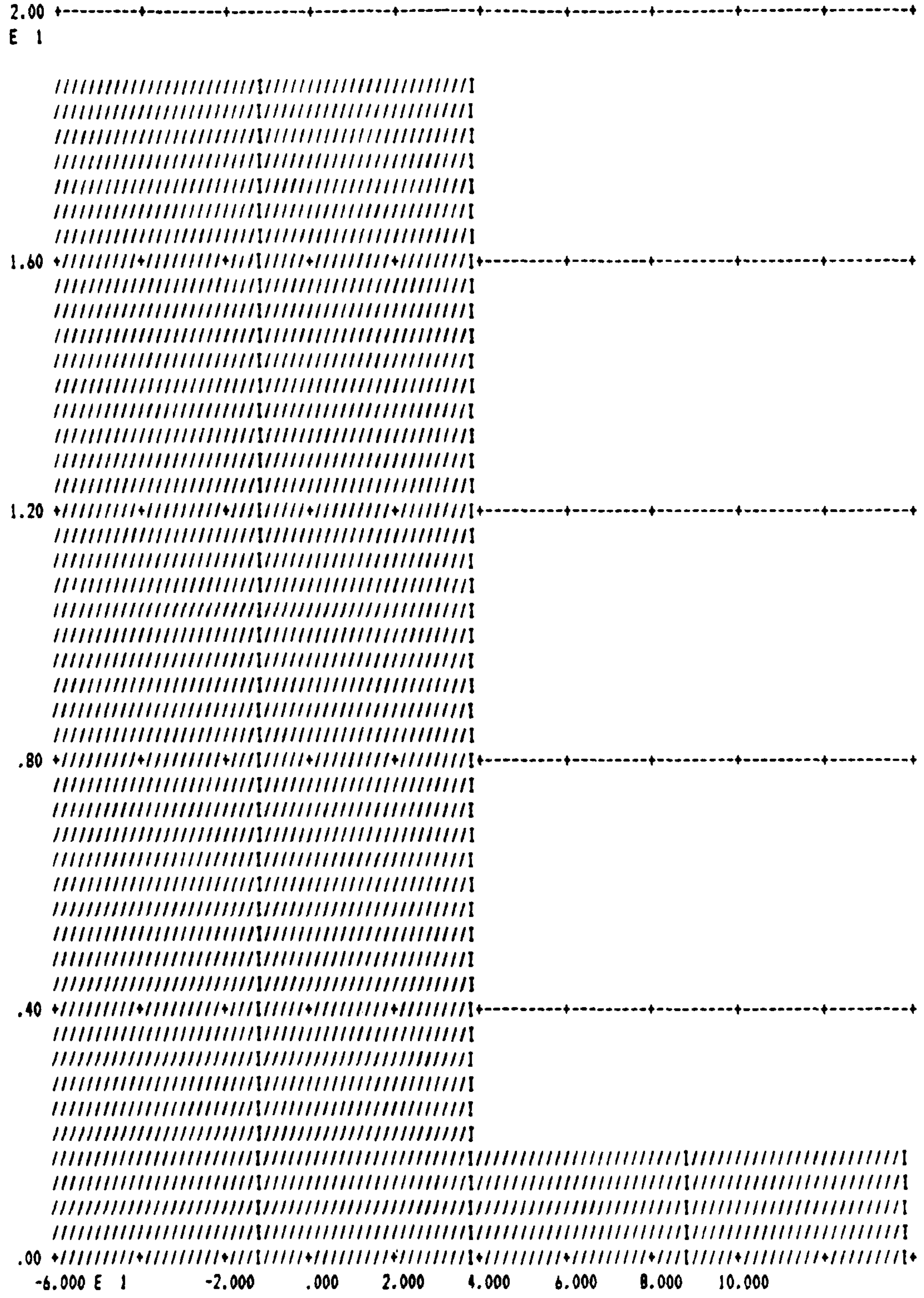

Figure 69. Estimated Residuals Histogram for NSN 12

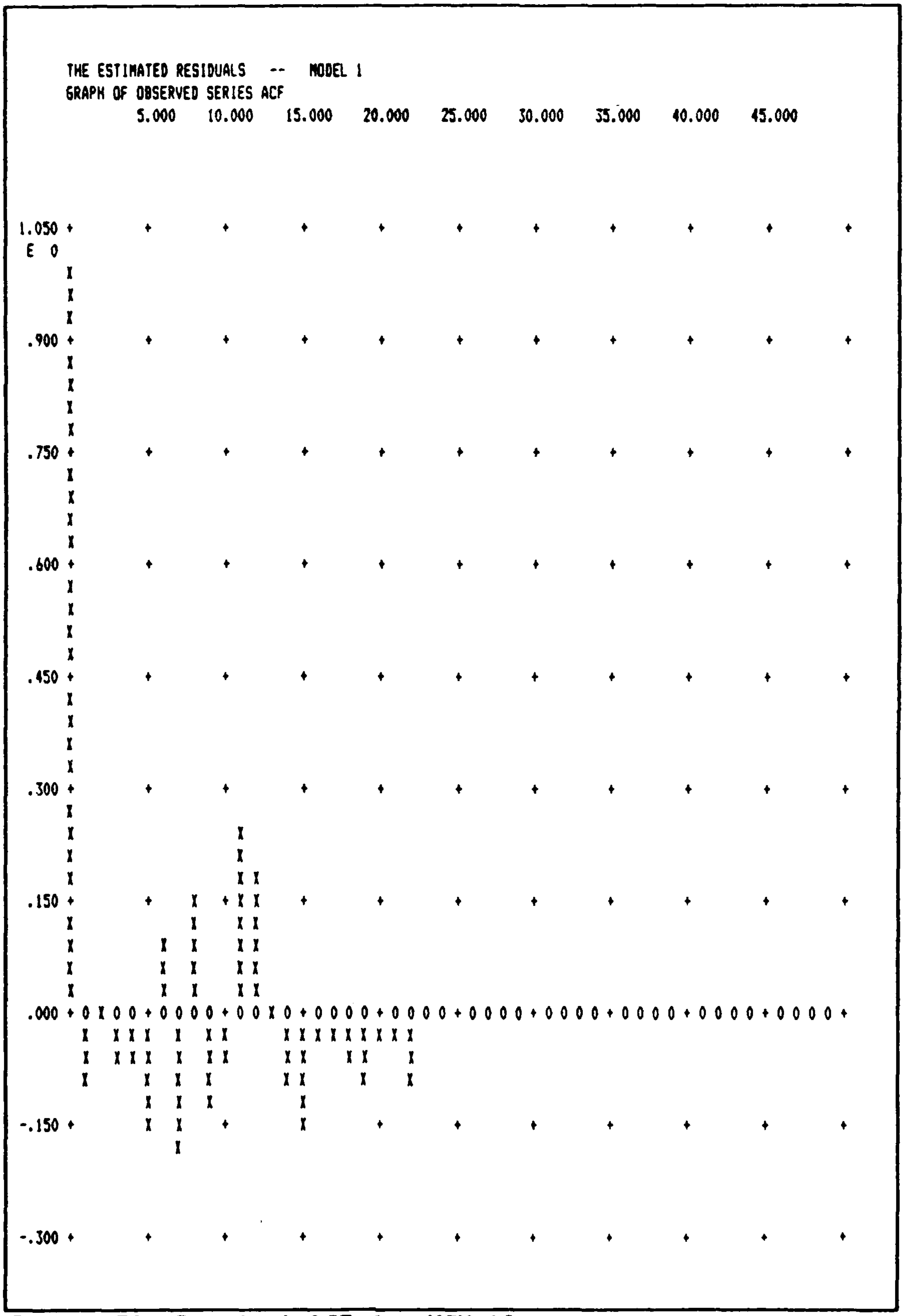

Figure 70. Residual ACF for NSN 12

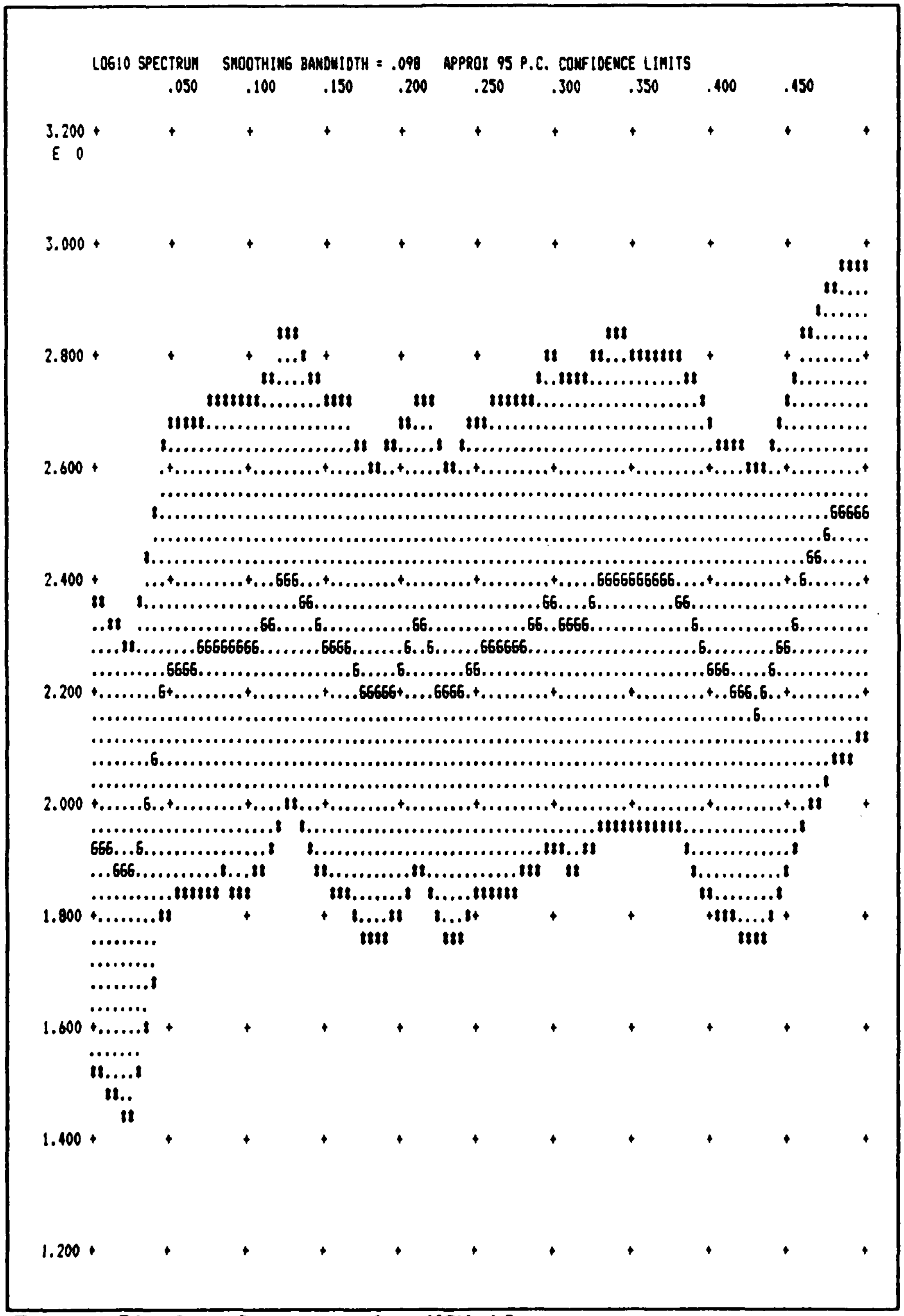

Figure 71. Log Spectrum for NSN 12

Attachment 10: December Forecasts

	Jan	Feb	Mar	Apr
NSN 1				
Simple Exp.	12.2	12.2	12.2	12.2
Winters' Exp.	15.49	20.85	6.59	4.68
Box-Jenkins	14.25	9.47	9.77	11.33
SBSS	12.07	12.07	12.07	12.07
Actuals	7	10	9	5
NSN 2				
Simple Exp.	2	2	2	2
Winters' Exp.	2.96	4.13	4.72	3.46
Box-Jenkins				
SBSS	2.05	2.05	2.05	2.05
Actuals	0	1	0	1
NSN 3				
Simple Exp.	89.35	89.35	89.35	89.35
Winters' Exp.	82.1	86.49	57.66	36.35
Box-Jenkins	98.05	104.38	104.38	104.38
SBSS	111.44	111.44	111.44	111.44
Actuals	77	63	49	25
NSN 4				
Simple Exp.	6.89	6.89	6.89	6.89
Winters' Exp.	5.87	6.11	3.31	2.72
Box-Jenkins				
SBSS	9.82	9.82	9.82	9.82
Actuals	5	6	1	1
NSN 5				
Simple Exp.	18.8	18.8	18.8	18.8
Winters' Exp.	22.66	54.82	10.45	7.63
Box-Jenkins	6.2	8.09	-0.52	1.52
SBSS	18.27	18.27	18.27	18.27
Actuals	5	1	0	1
NSN 6				
Simple Exp.	12.43	12.43	12.43	12.43
Winters' Exp.	16.82	18.7	17.83	15.64
Box-Jenkins				
SBSS	11.27	11.27	11.27	11.27
Actuals	0	2	0	0

December Forecasts

	Jan	Feb	Mar	Apr
NSN 7				
Simple Exp.	9.79	9.79	9.79	9.79
Winters' Exp.	15.48	35.24	4.72	3.06
Box-Jenkins				
SBSS	9.67	9.67	9.67	9.67
Actuals	2	1	0	1
NSN 8				
Simple Exp.	177.3	177.3	177.3	177.3
Winters' Exp.	237.58	202.12	183.18	107.78
Box-Jenkins				
SBSS	131.49	131.49	131.49	131.49
Actuals	873	161	54	47
NSN 9				
Simple Exp.	13.52	13.52	13.52	13.52
Winters' Exp.	20.97	8.65	10.38	8.59
Box-Jenkins	35.87	22.07	18.99	23.77
SBSS	13.63	13.63	13.63	13.63
Actuals	53	12	2	3
NSN 10				
Simple Exp.	54.95	54.95	54.95	54.95
Winters' Exp.	58.81	54.11	54.66	33.56
Box-Jenkins	92.85	99.37	99.37	99.37
SBSS	62.28	62.28	62.28	62.28
Actuals	81	33	28	17
NSN 11				
Simple Exp.	9.68	9.68	9.68	9.68
Winters' Exp.	13.7	13.18	9.84	2.91
Box-Jenkins	3.93	7.38	5.56	3.96
SBSS	8.37	8.37	8.37	8.37
Actuals	6	4	4	5
NSN 12				
Simple Exp.	13.98	13.98	13.98	13.98
Winters' Exp.	28.12	40.83	21.59	5.31
Box-Jenkins	41.38	35	18.25	15.48
SBSS	19.69	19.69	19.69	19.69
Actuals	23	18	31	13

<u>Attachment 10: January Forecasts</u>

	Feb	Mar	Apr
NSN 1			
Simple Exp.	11.9	11.9	11.9
Winters' Exp.	18.52	5.25	3.47
Box-Jenkins	6.07	6.93	6.81
SBSS	11.7	11.7	11.7
Actuals	10	9	5
NSN 2			
Simple Exp.	1.84	1.84	1.84
Winters' Exp.	2.94	3.3	2.24
Box-Jenkins			
SBSS	1.92	1.92	1.92
Actuals	1	0	1
NSN 3			
Simple Exp.	90.51	90.51	90.51
Winters' Exp.	89.38	60.42	39.1
Box-Jenkin	98.3	104.38	104.38
SBSS	108.74	108.74	108.74
Actuals	63	49	25
NSN 4			
Simple Exp.	5.6	5.6	5.6
Winters' Exp.	5.15	2.56	1.86
Box-Jenkinsns			
SBSS	9.48	9.48	9.48
Actuals	6	1	1
NSN 5			
Simple Exp.	18.16	18.16	18.16
Winters' Exp.	60.48	11.99	9.02
Box-Jenkins	7.4	-0.89	0.39
SBSS	17.39	17.39	17.39
Actuals	1	0	1
NSN 6			
Simple Exp.	10.66	10.66	10.66
Winters' Exp.	5.43	5.37	3.74
Box-Jenkins			
SBSS	10.54	10.54	10.54
Actuals	2	0	0

January Forecasts

	Feb	Mar	Apr
NSN 7			
Simple Exp.	9.4	9.4	9.4
Winters' Exp.	35.73	4.02	2.39
Box-Jenkins			
SBSS	9.14	9.14	9.14
Actuals	1	0	1
NSN 8			
Simple Exp.	233.67	233.67	233.67
Winters' Exp.	386.42	298.51	181.22
Box-Jenkins			
SBSS	173.75	173.75	173.75
Actuals	161	54	47
NSN 9			
Simple Exp.	44.49	44.49	44.49
Winters' Exp.	19.9	21.66	19.83
Box-Jenkins	38.35	17.47	27.4
SBSS	15.77	15.77	15.77
Actuals	12	2	3
NSN 10			
Simple Exp.	60.68	60.68	60.68
Winters' Exp.	64.95	63.57	45.91
Box-Jenkins	95.25	100.23	100.23
SBSS	62.98	62.98	62.98
Actuals	33	28	17
NSN 11			
Simple Exp.	10.48	10.48	10.48
Winters' Exp.	14.1	10.63	3.41
Box-Jenkins	7.38	5.56	2.02
SBSS	8.47	8.47	8.47
Actuals	4	4	5
NSN 12			
Simple Exp.	21.62	21.62	21.62
Winters' Exp.	41.81	22.06	5.5
Box-Jenkins	35	18.25	12.39
SBSS	19.76	19.76	19.76
Actuals	18	31	13

Attachment 11: February Forecasts

	Mar	Apr
NSN 1		
Simple Exp.	11.98	11.98
Winters' Exp.	6.2	4.27
Box-Jenkins	8.77	8.31
SBSS	12.44	12.44
Actuals	0	5
NSN 2		
Simple Exp.	1.87	1.87
Winters' Exp.	2.98	2.09
Box-Jenkins		
SBSS	2	2
Actuals	0	1
NSN 3		
Simple Exp.	85.39	85.39
Winters' Exp.	56.61	35.88
Box-Jenkins	94.18	104.38
SBSS	113.82	113.82
Actuals	49	25
NSN 4		
Simple Exp.	5.87	5.87
Winters' Exp.	2.79	2.12
Box-Jenkins		
SBSS	9.95	9.95
Actuals	1	1
NSN 5		
Simple Exp.	17.13	17.13
Winters' Exp.	11.01	7.67
Box-Jenkins	-4.55	-1.58
SBSS	17.67	17.67
Actuals	0	1
NSN 6		
Simple Exp.	10.26	10.26
Winters' Exp.	6.69	4.9
Box-Jenkins		
SBSS	10.79	10.79
Actuals	0	0

February Forecasts

	Mar	Apr
NSN 7		
Simple Exp.	8.99	8.99
Winters' Exp.	3.57	2.06
Box-Jenkins		
SBSS	9.31	9.31
Actuals	0	1
NSN 8		
Simple Exp.	222.41	222.41
Winters' Exp.	178.3	93.7
Box-Jenkins		
SBSS	185.41	185.41
Actuals	54	47
NSN 9		
Simple Exp.	13.04	13.04
Winters' Exp.	10.05	8.22
Box-Jenkins	11.1	28.94
SBSS	16.68	16.68
Actuals	2	3
NSN 10		
Simple Exp.	56.38	56.38
Winters' Exp.	56.41	37.03
Box-Jenkins	78.59	104.73
SBSS	65.71	65.71
Actuals	28	17
NSN 11		
Simple Exp.	9.25	9.25
Winters' Exp.	9.16	2.21
Box-Jenkins	5.56	2.02
SBSS	8.82	8.82
Actuals	4	5
NSN 12		
Simple Exp.	18.55	18.55
Winters' Exp.	20.46	4.96
Box-Jenkins	18.25	12.39
SBSS	21.06	21.06
Actuals	31	13

Attachment 12: March Forecasts

	Apr
NSN 1	
Simple Exp.	11.8
Winters' Exp.	4.07
Box-Jenkins	8.44
SBSS	12.25
Actuals	5
NSN 2	
Simple Exp.	1.73
Winters' Exp.	1.44
Box-Jenkins	
SBSS	1.89
Actuals	1
NSN 3	
Simple Exp.	30.3
Winters' Exp.	32.75
Box-Jenkins	91.33
SBSS	110.22
Actuals	25
NSN 4	
Simple Exp.	2.54
Winters' Exp.	1.2
Box-Jenkins	
SBSS	9.45
Actuals	1
NSN 5	
Simple Exp.	16.4
Winters' Exp.	6.42
Box-Jenkins	1.03
SBSS	16.68
Actuals	1
NSN 6	
Simple Exp.	9.64
Winters' Exp.	3.48
Box-Jenkins	
SBSS	10.19
Actuals	0

March Forecasts

	Apr
NSN 7	
Simple Exp.	8.57
Winters' Exp.	1.38
Box-Jenkins	
SBSS	8.79
Actuals	1
NSN 8	
Simple Exp.	208.88
Winters' Exp.	71.3
Box-Jenkins	
SBSS	178.11
Actuals	47
NSN 9	
Simple Exp.	5.23
Winters' Exp.	5.32
Box-Jenkins	25.39
SBSS	15.86
Actuals	3
NSN 10	
Simple Exp.	54.83
Winters' Exp.	35.45
Box-Jenkins	87.14
SBSS	63.62
Actuals	17
NSN 11	
Simple Exp.	9.09
Winters' Exp.	2.18
Box-Jenkins	2.02
SBSS	8.55
Actuals	5
NSN 12	
Simple Exp.	29.11
Winters' Exp.	5.6
Box-Jenkins	12.39
SBSS	21.62
Actuals	13

Attachment 13: Forecast Graphs

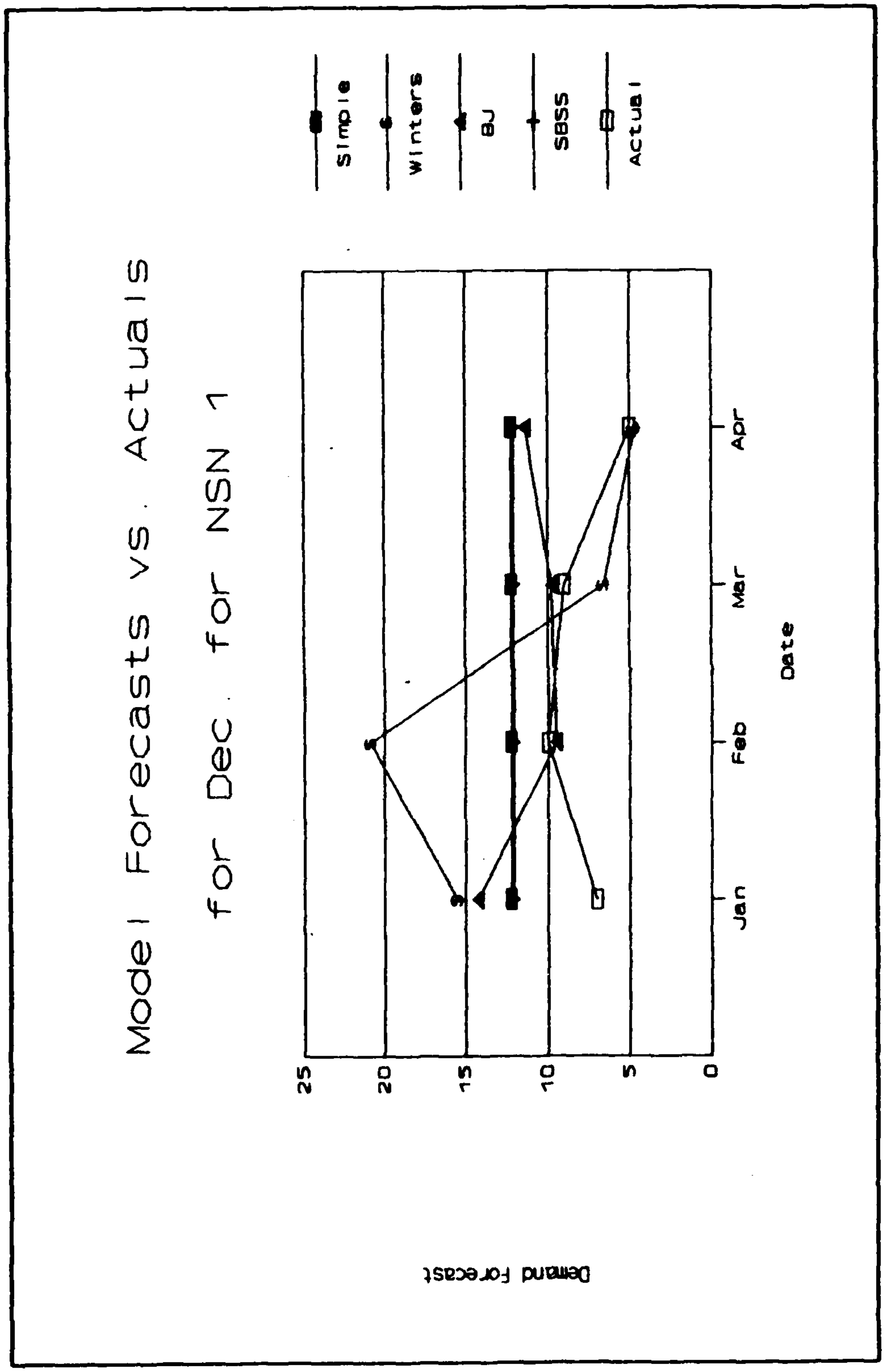

Figure 72. December Forecasts for NSN 1

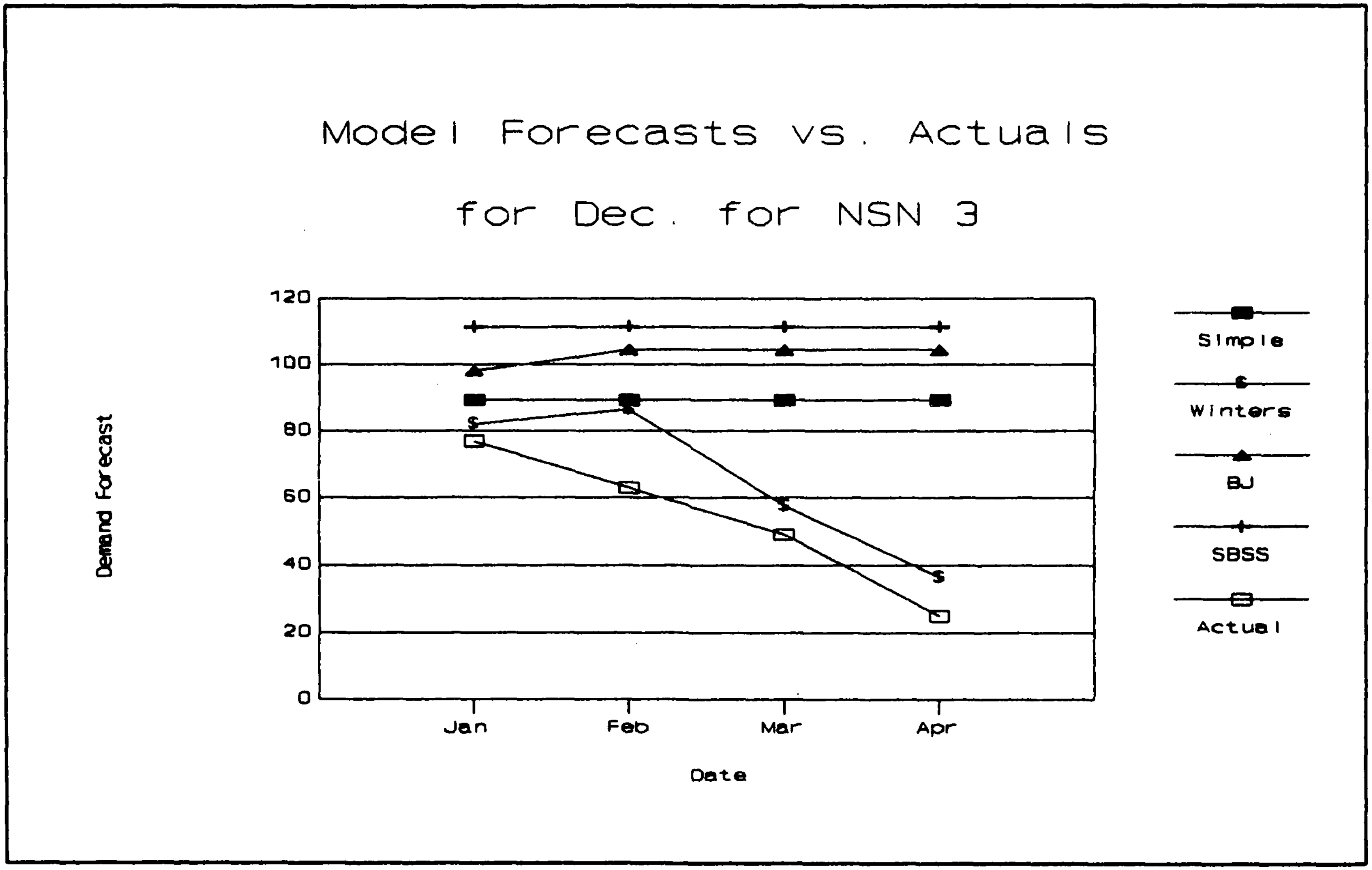

Figure 73. December Forecasts for NSN 3

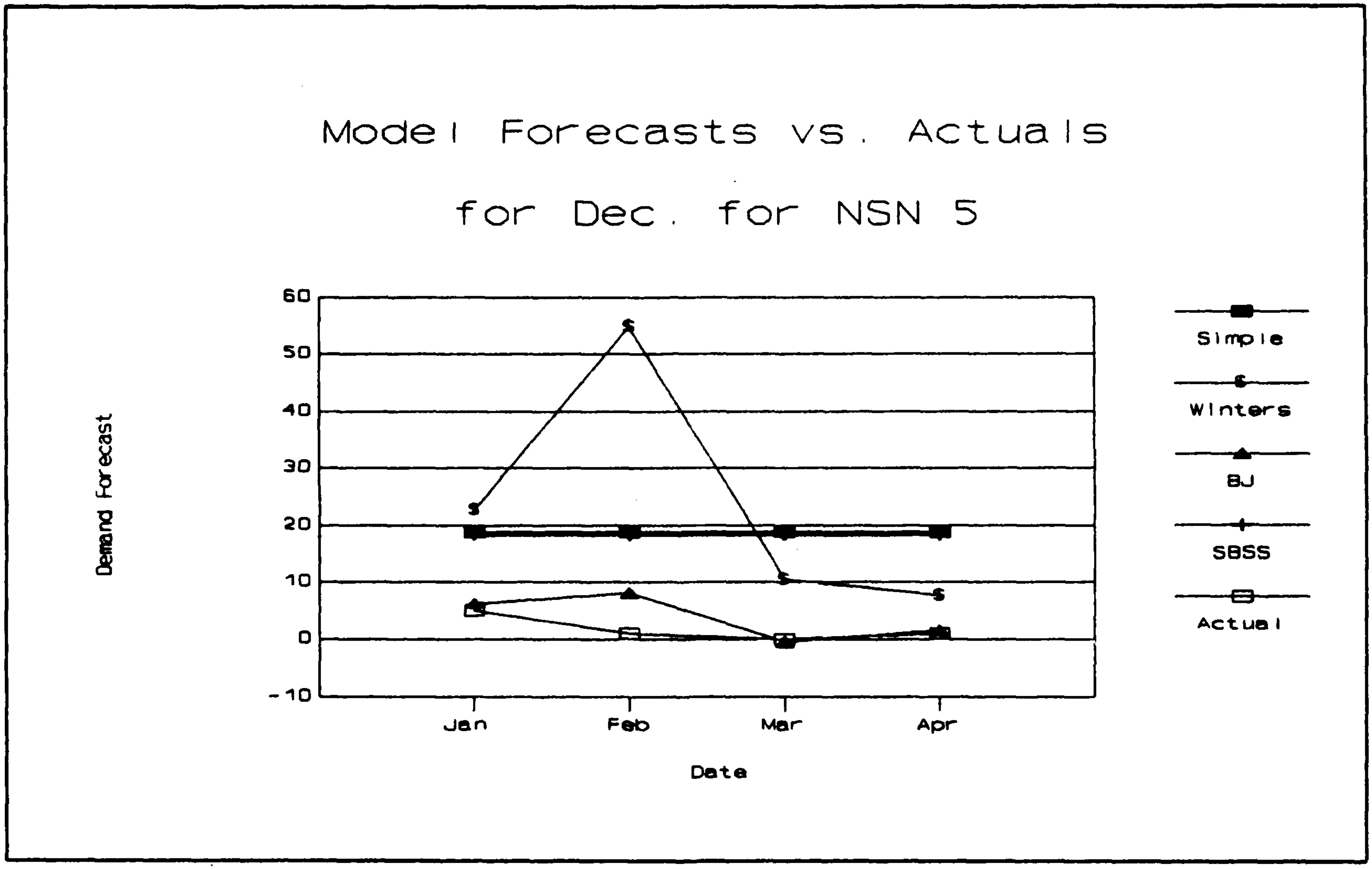

Figure 74. December Forecasts for NSN 5

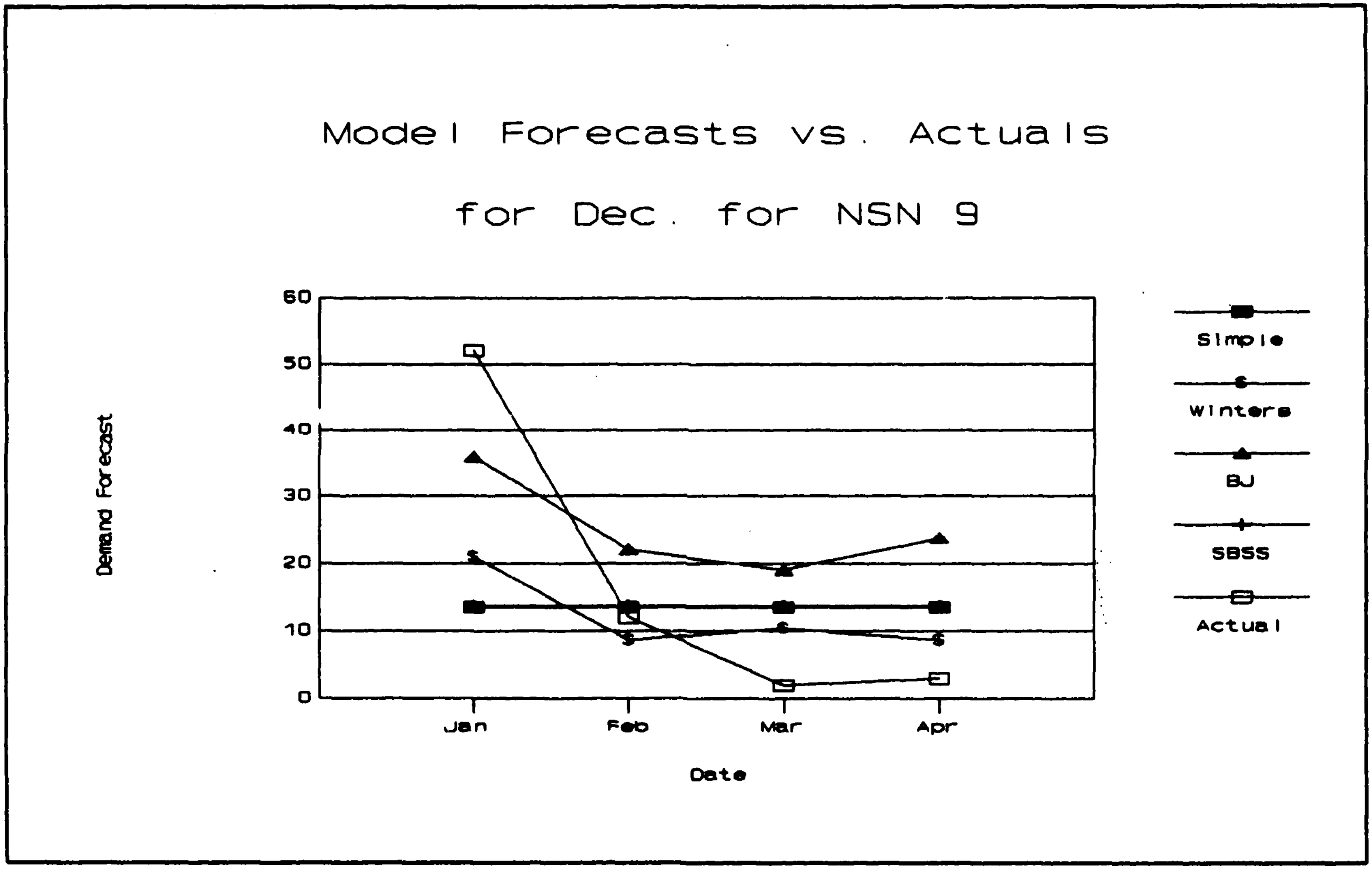

Figure 75. December Forecasts for NSN 9

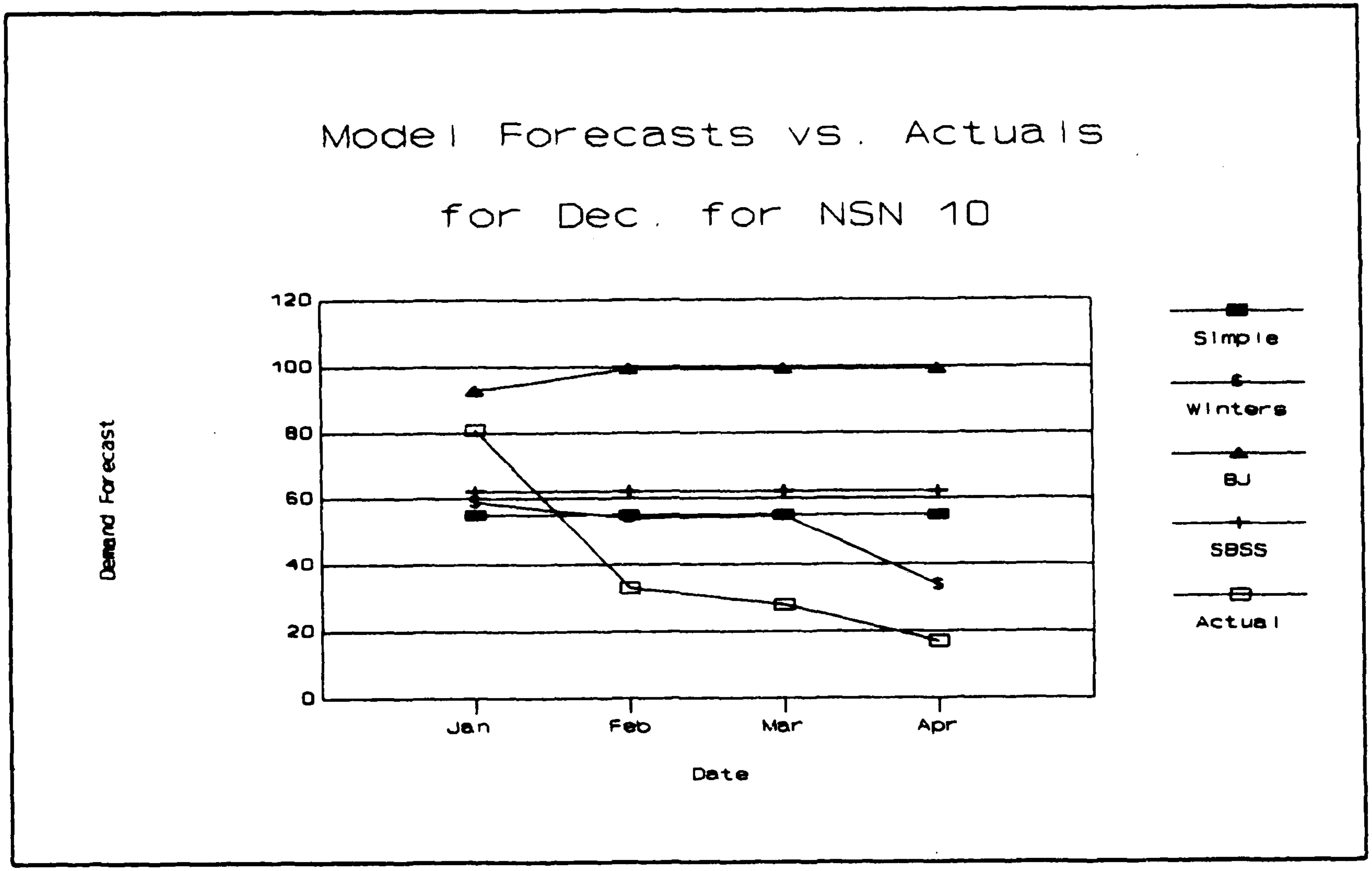

Figure 76. December Forecasts for NSN 10

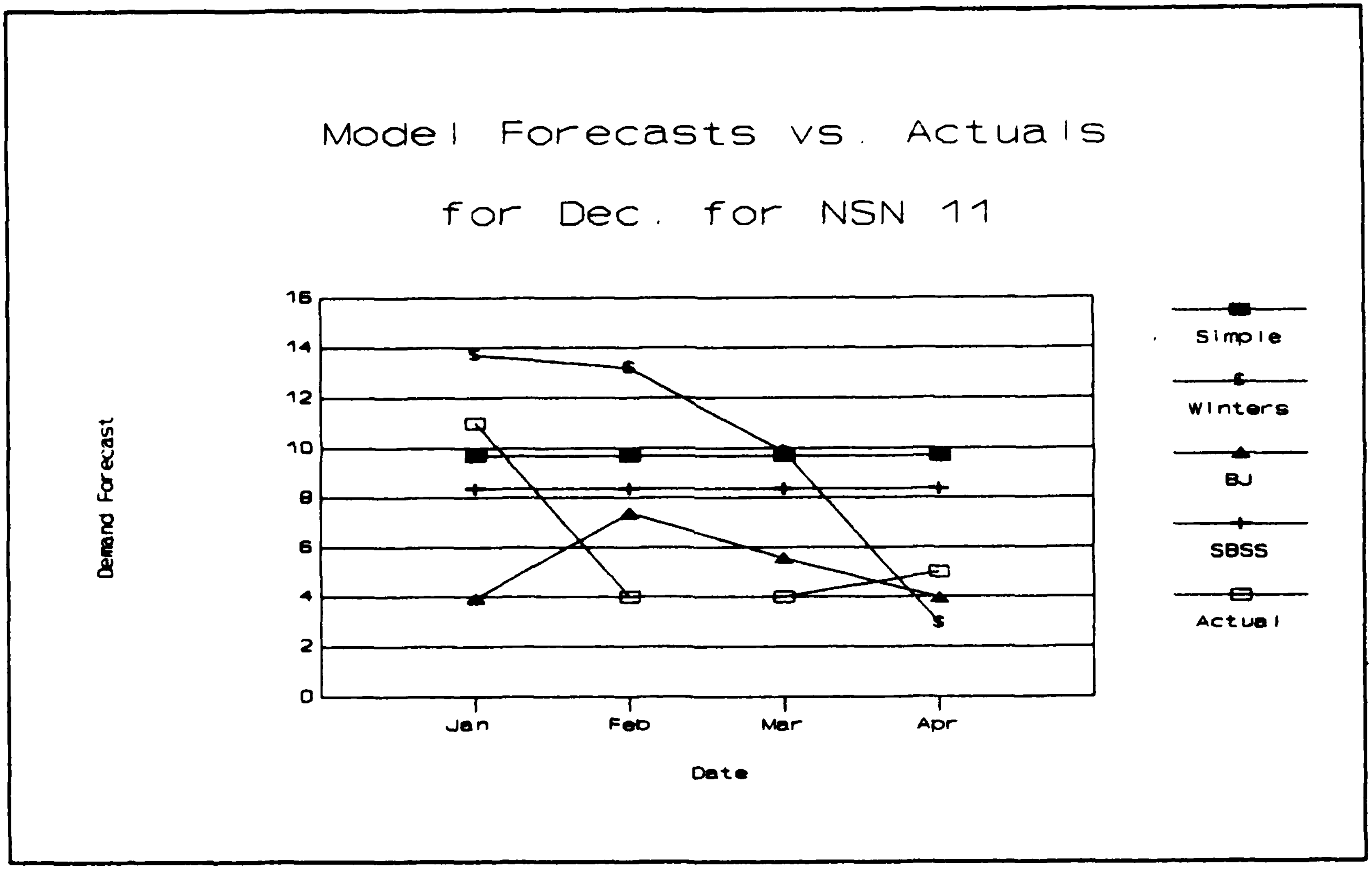

Figure 77. December Forecasts for NSN 11

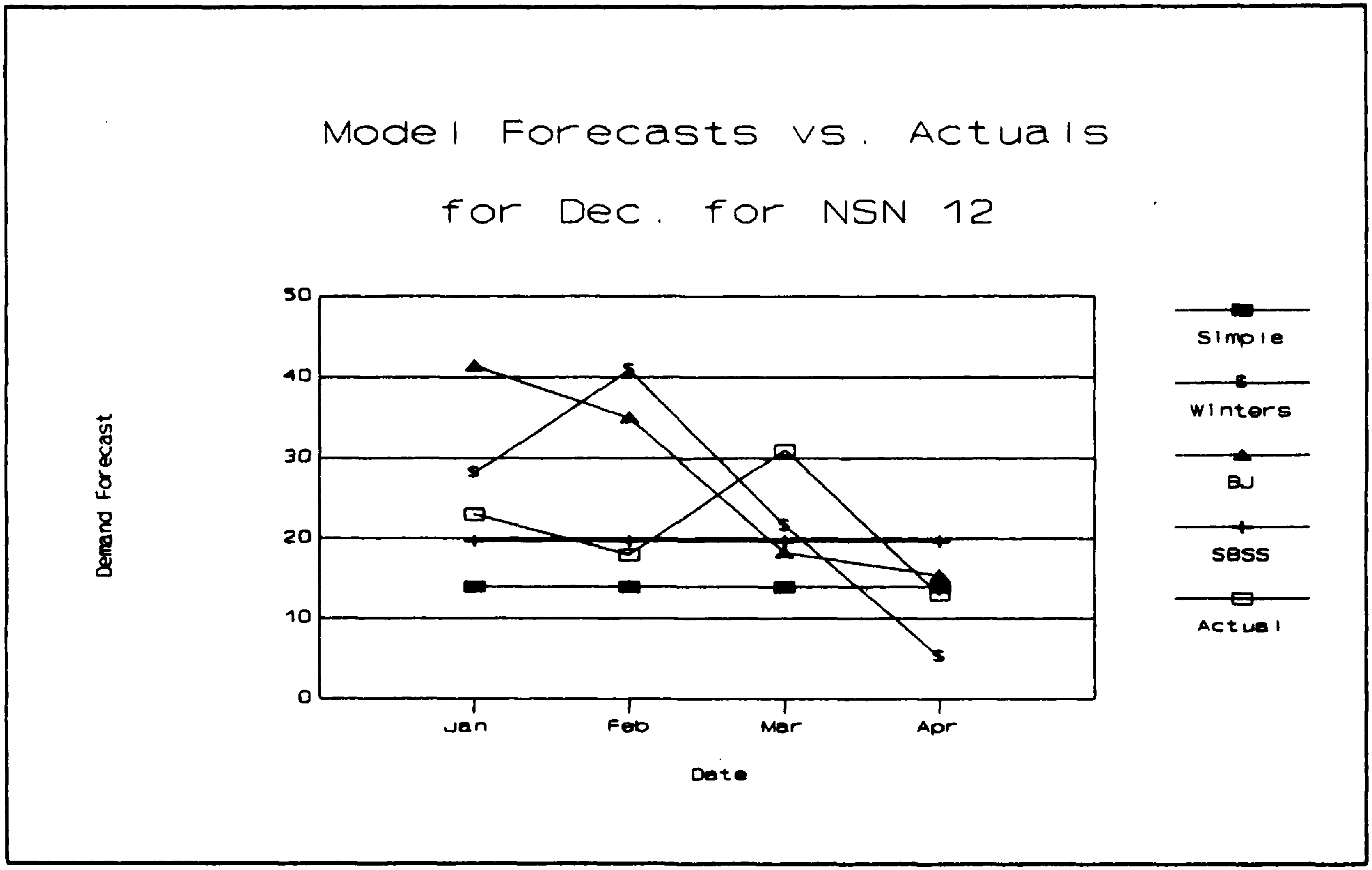

Figure 78. December Forecasts for NSN 12

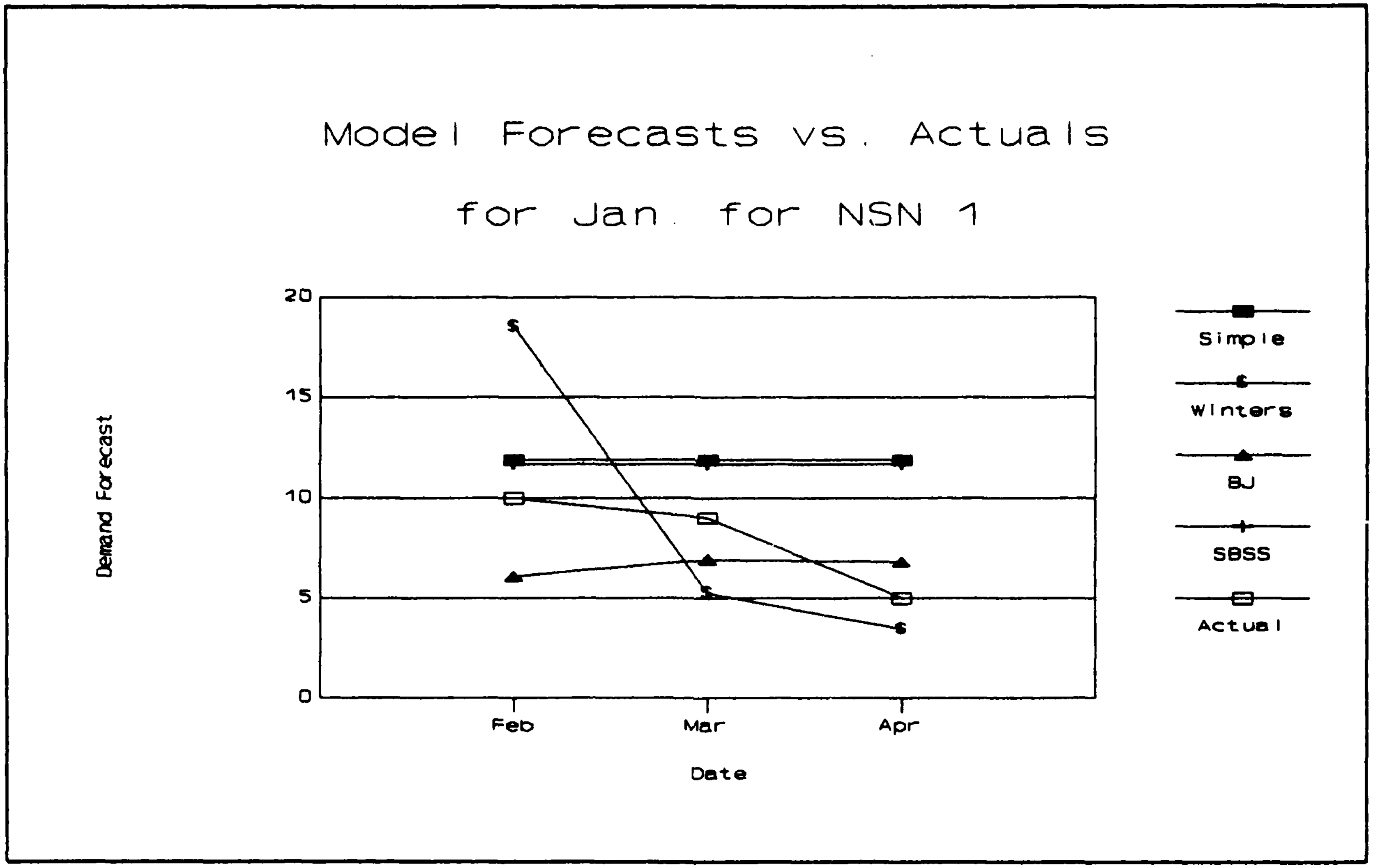

Figure 79. January Forecasts for NSN 1

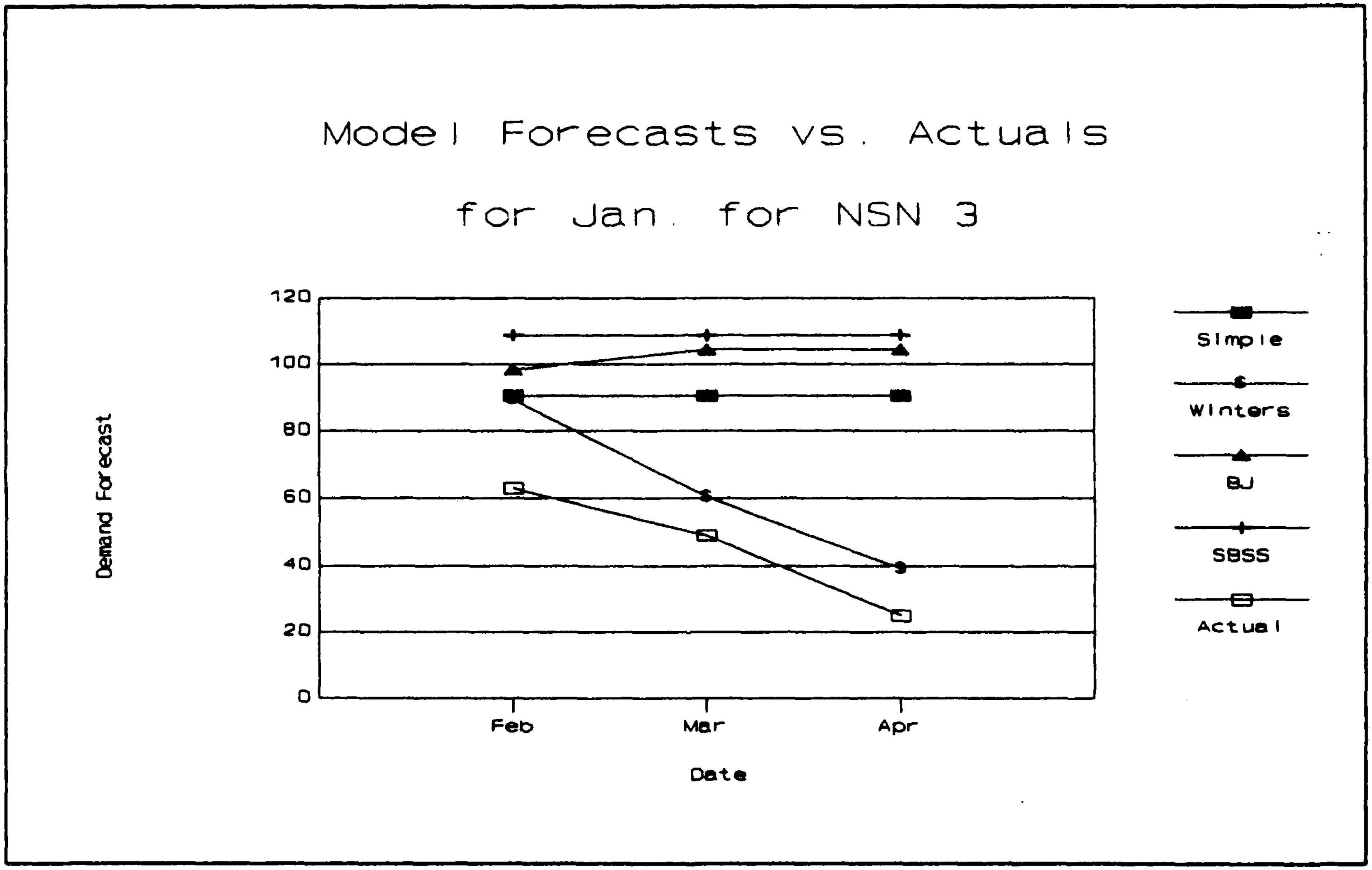

Figure 80. January Forecasts for NSN 3

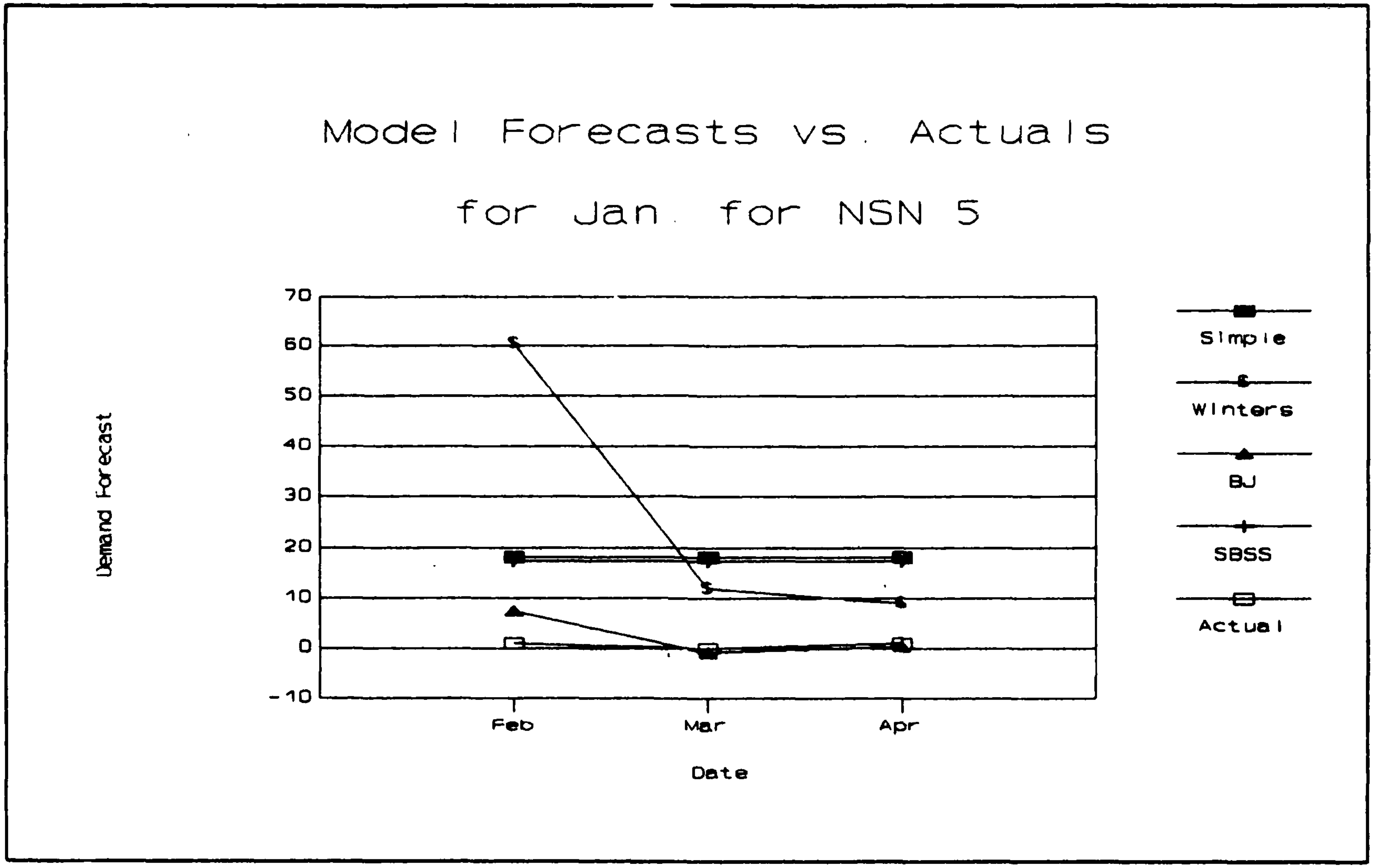

Figure 81. January Forecasts for NSN 5

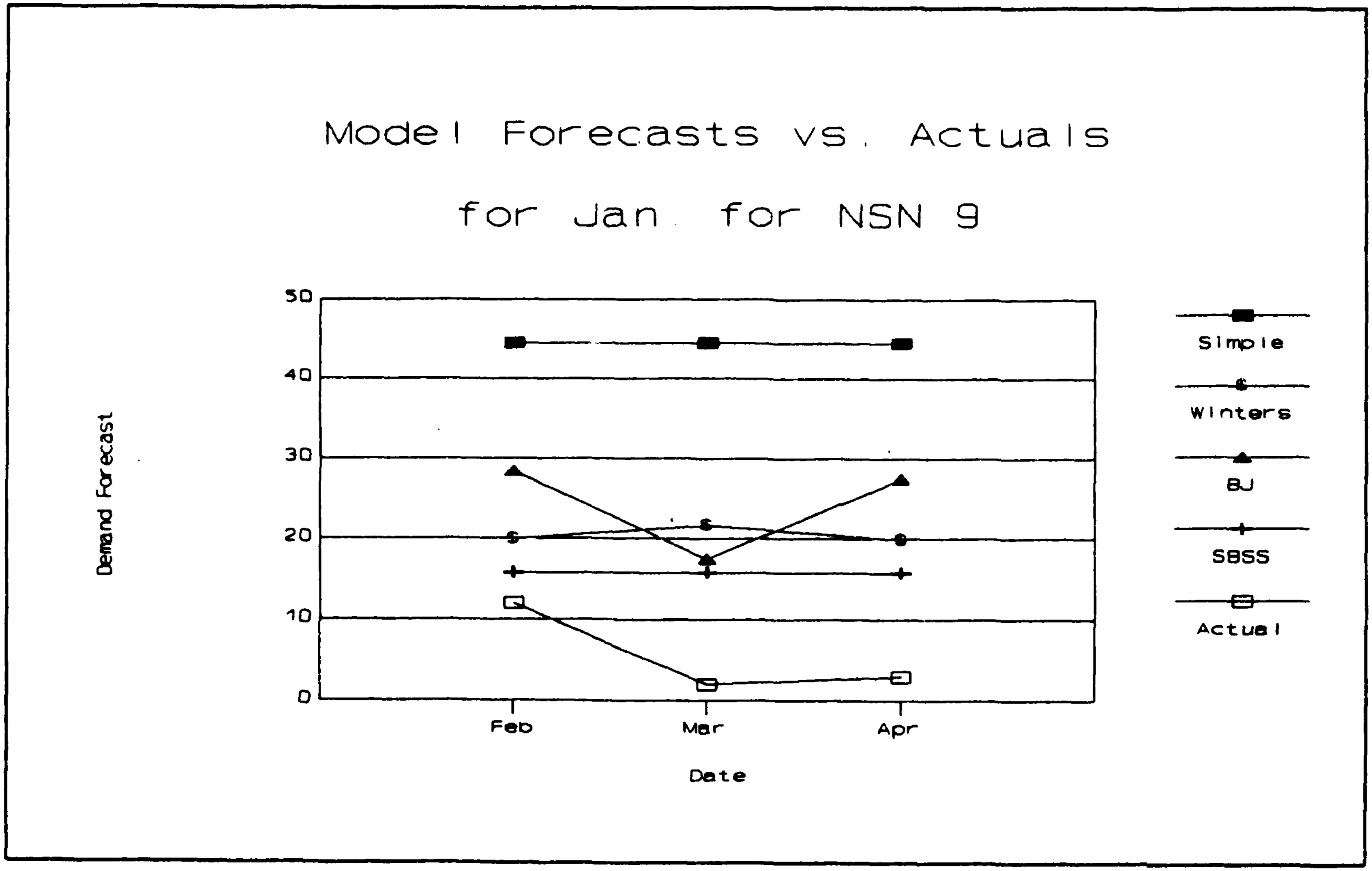

Figure 82. January Forecasts for NSN 9

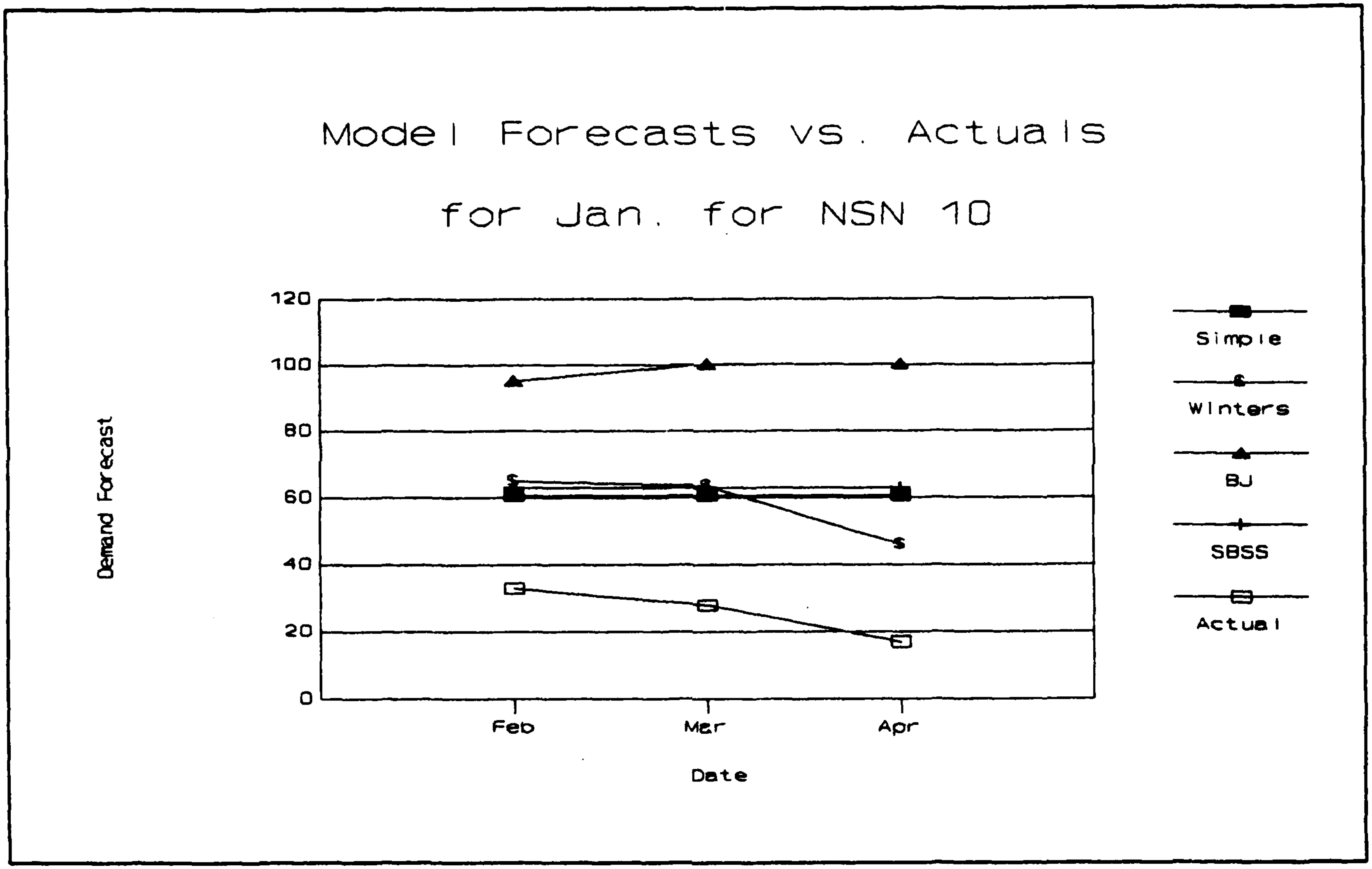

Figure 83. January Forecasts for NSN 10

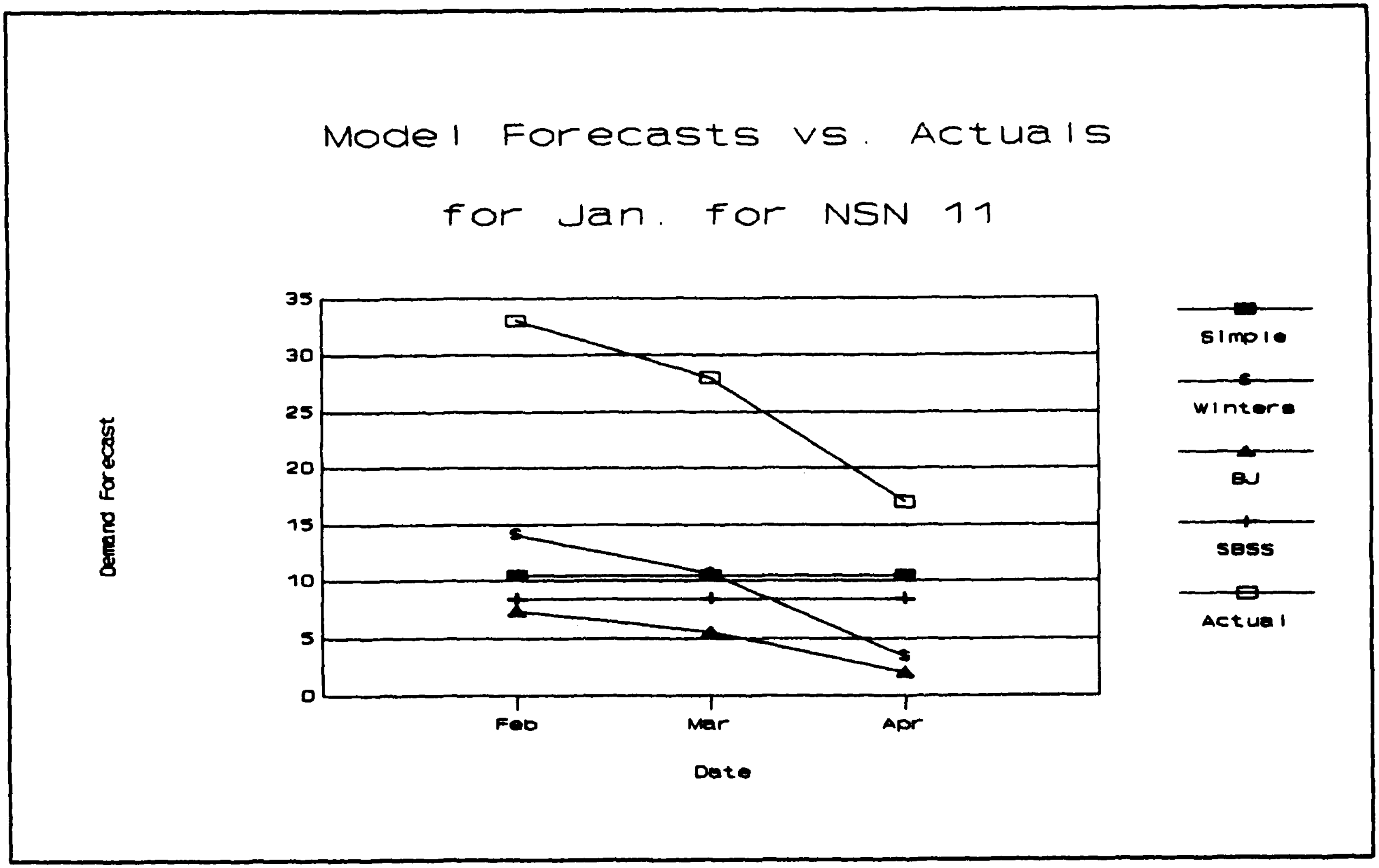

Figure 84. January Forecasts for NSN 11

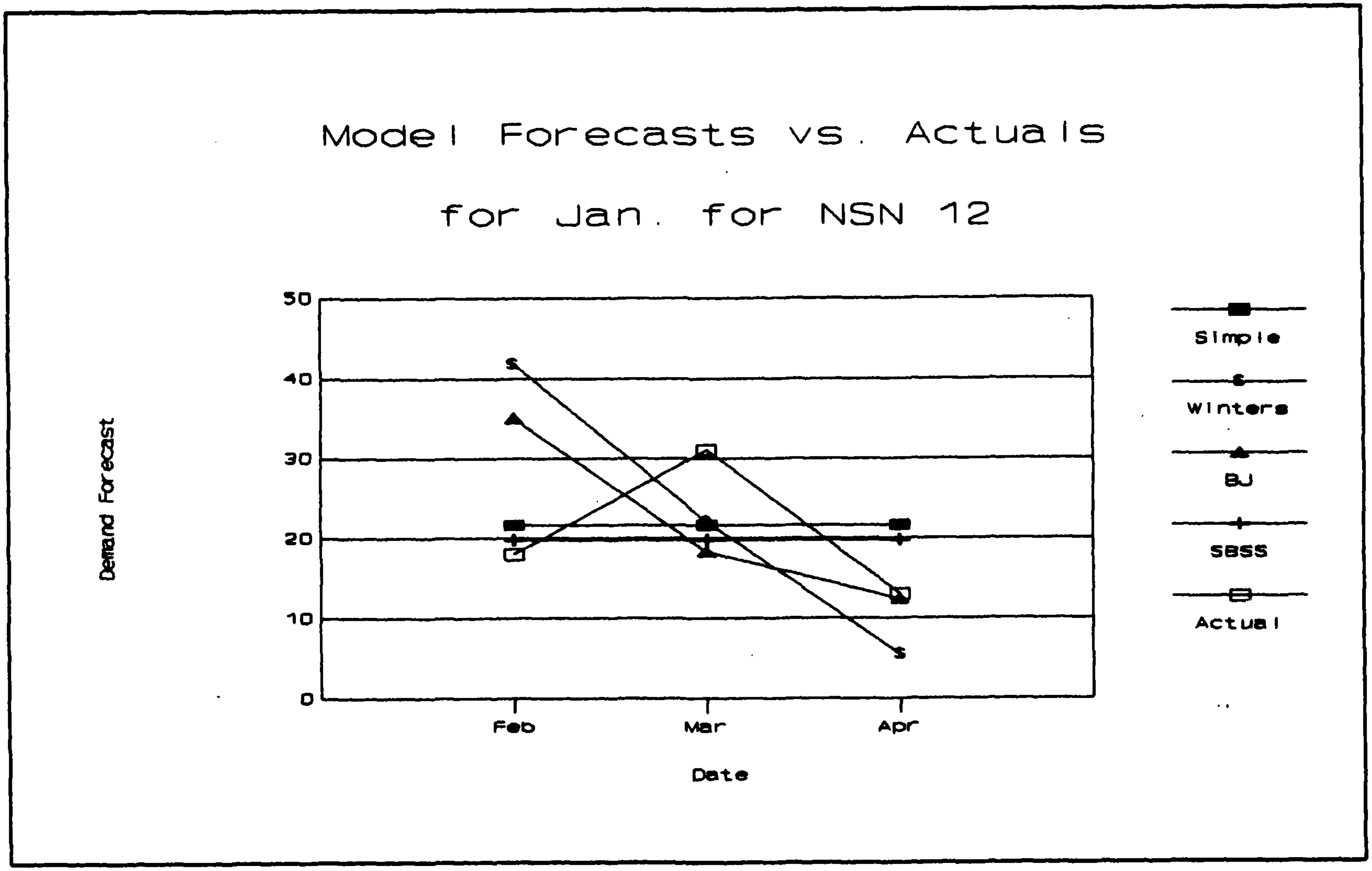

Figure 85. January Forecasts for NSN 12

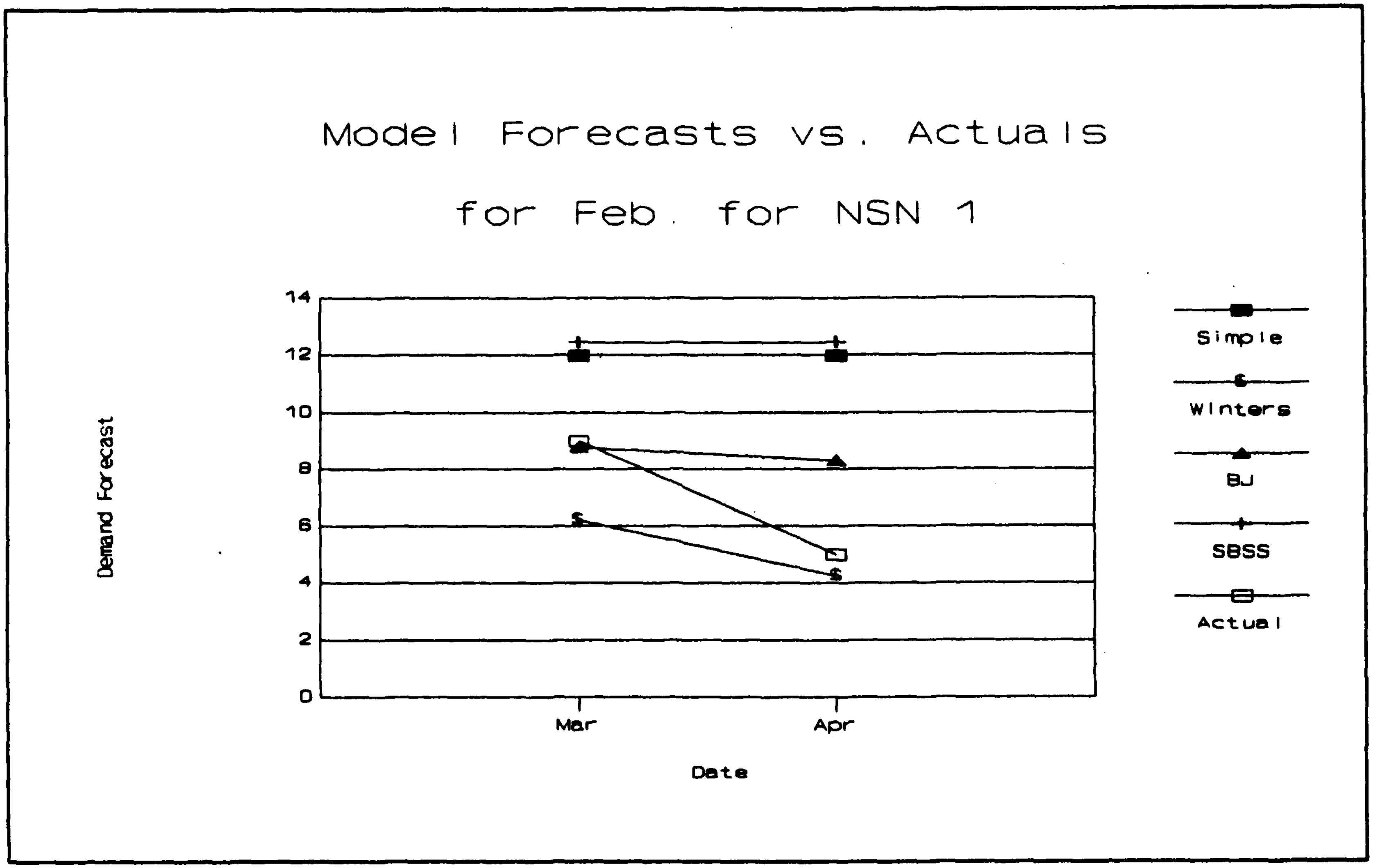

Figure 86. February Forecasts for NSN 1

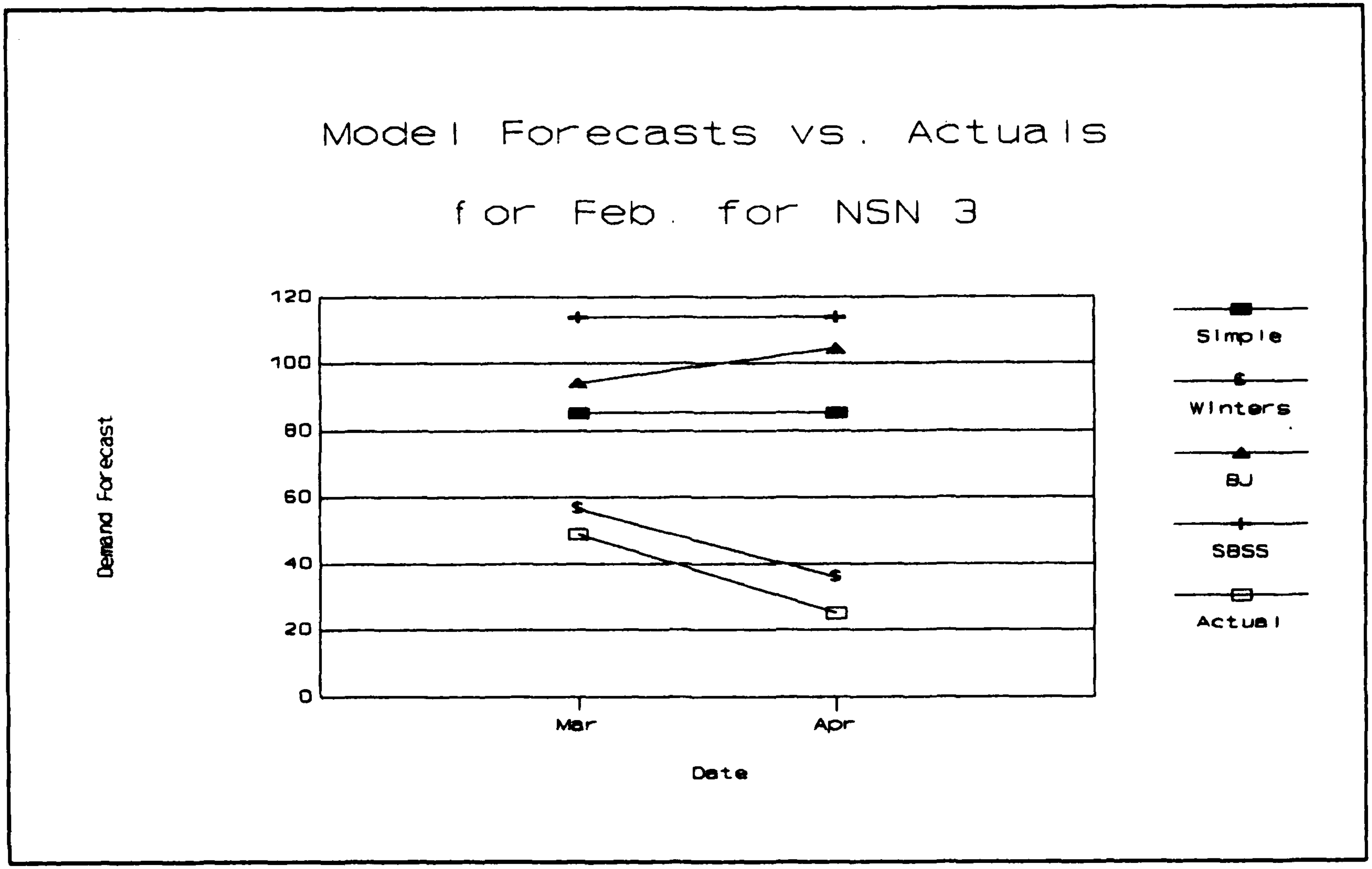

Figure 87. February Forecasts for NSN 3

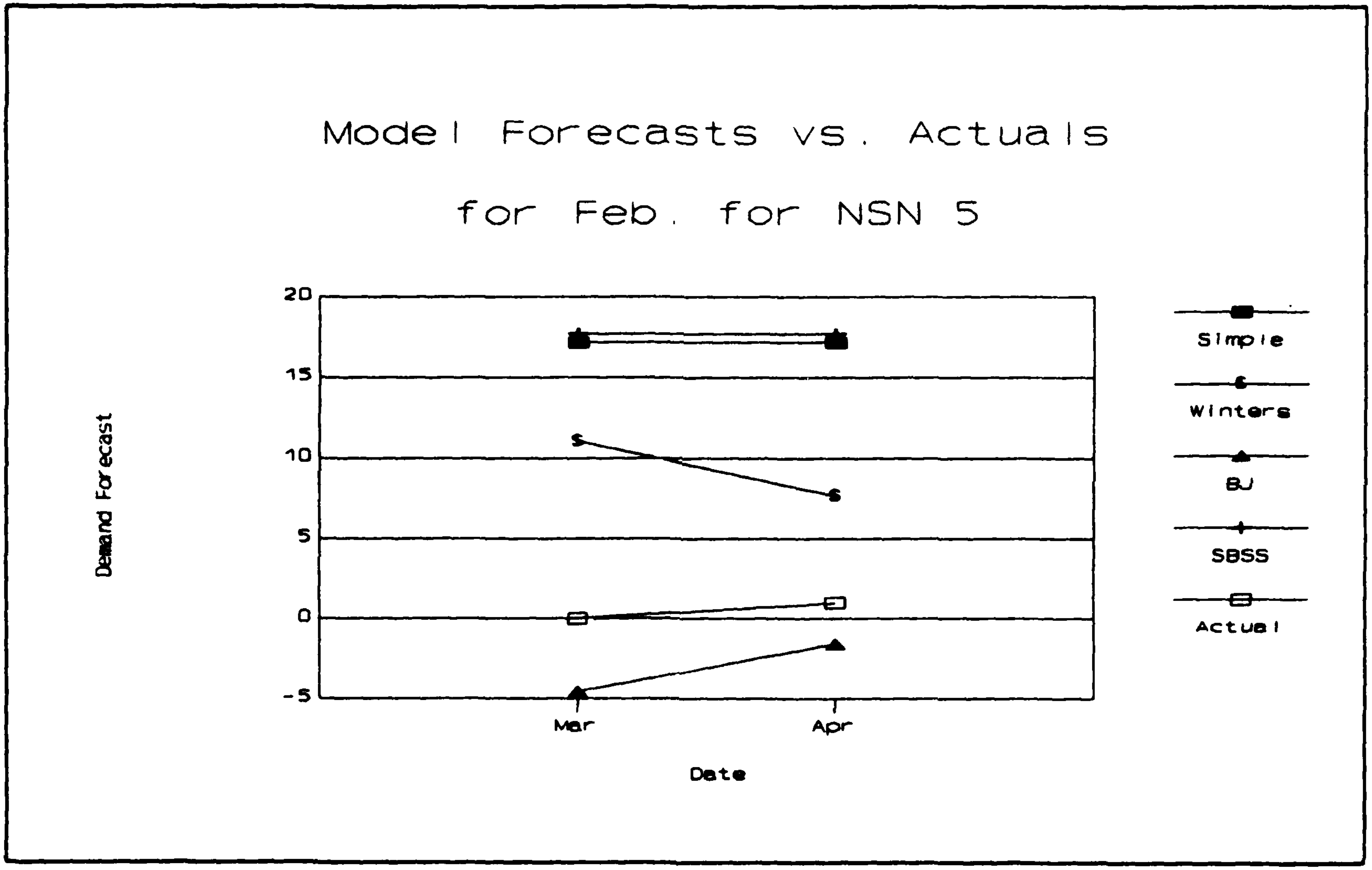

Figure 88. February Forecasts for NSN 5

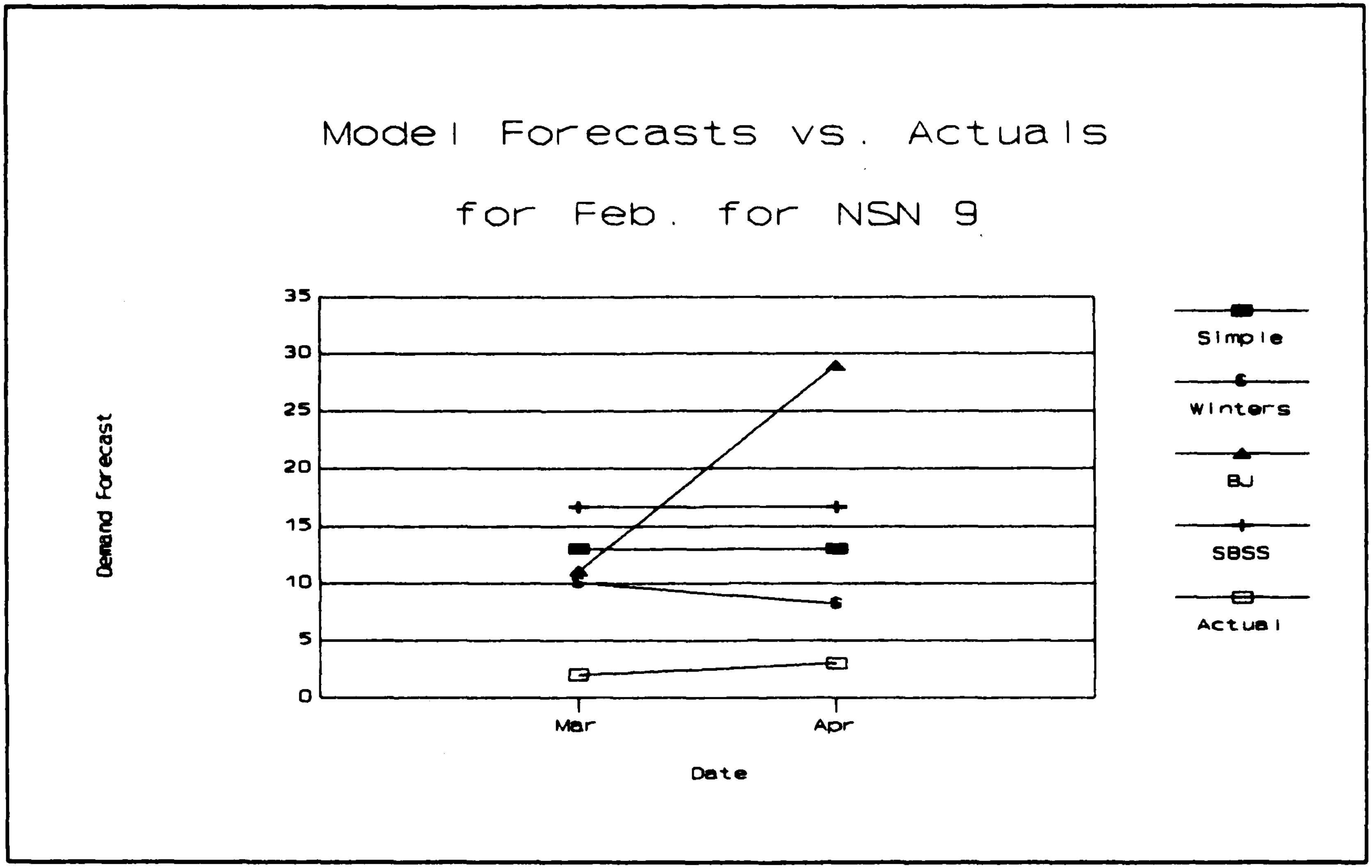

Figure 89. February Forecasts for NSN 9

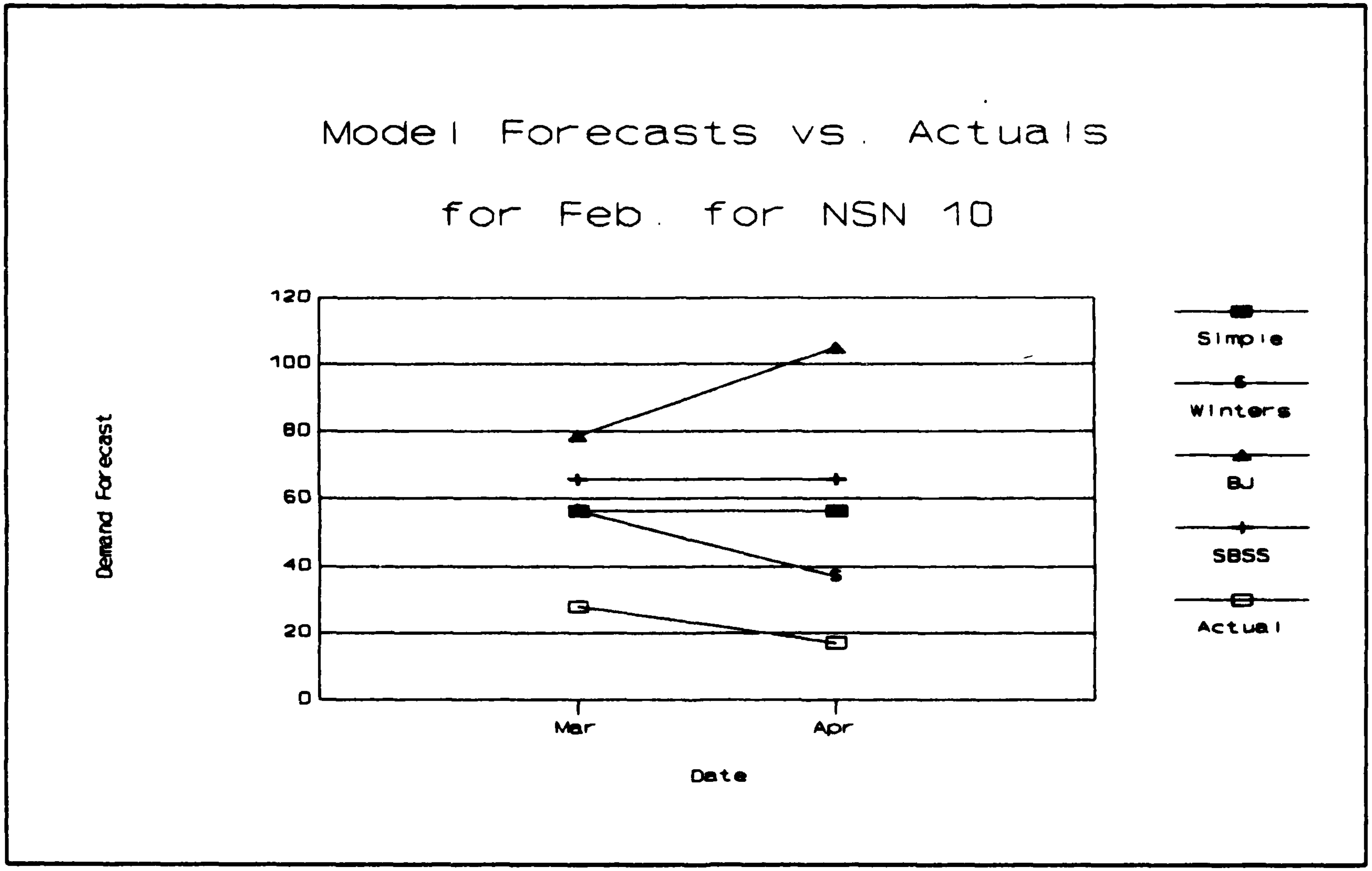

Figure 90. February Forecasts for NSN 10

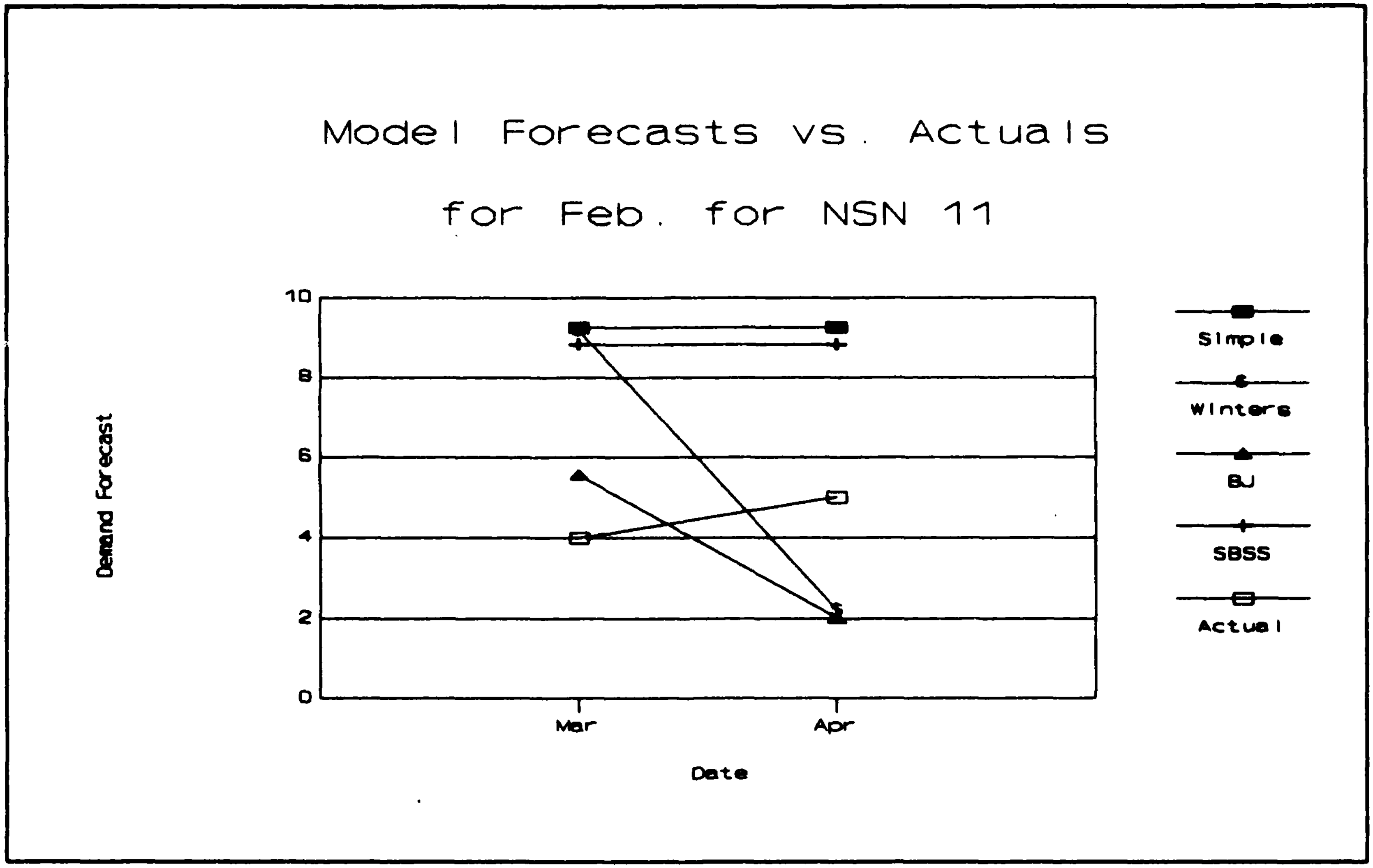

Figure 91. February Forecasts for NSN 11

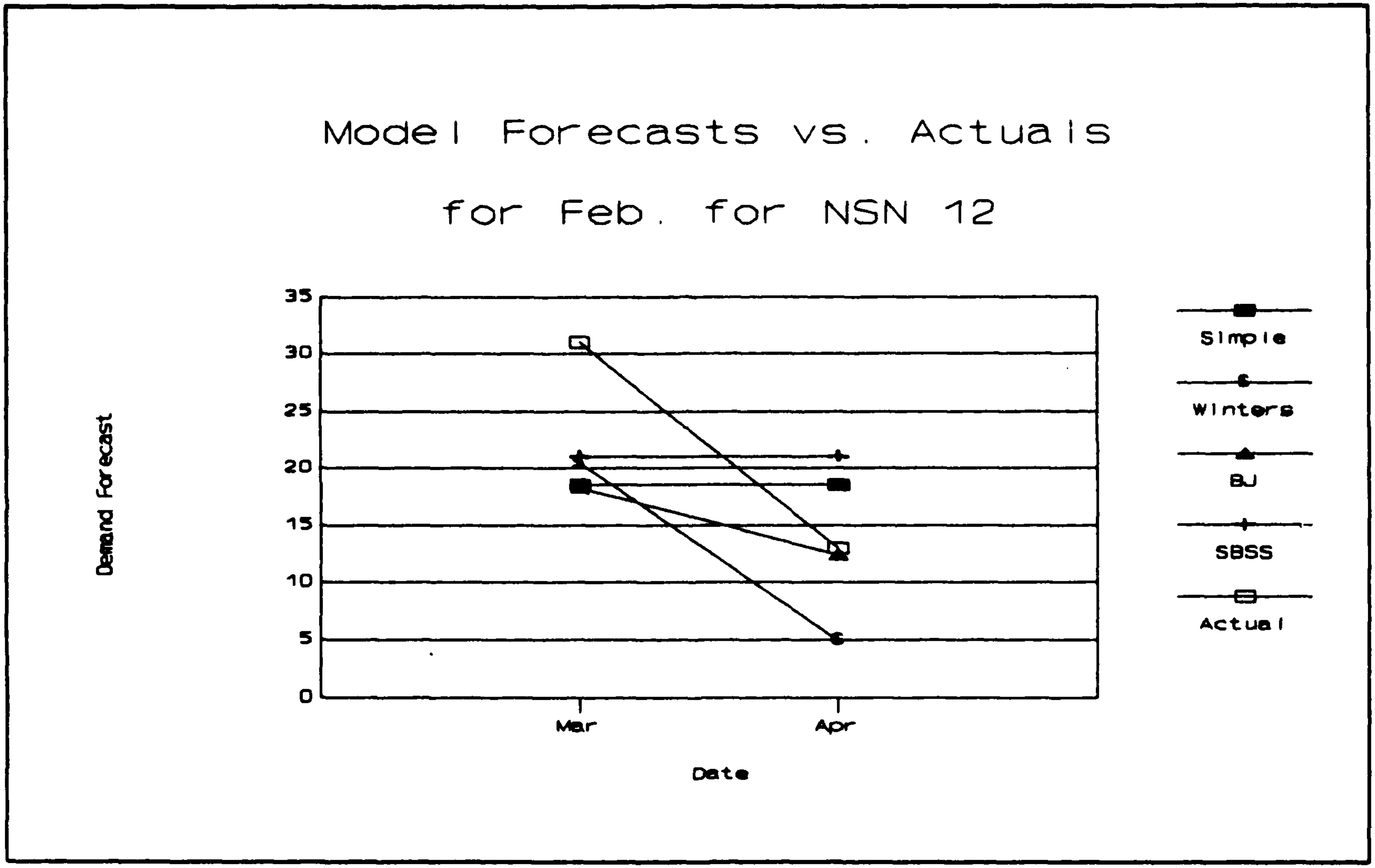

Figure 92. February Forecasts for NSN 12

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Vita

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This study investigated seasonally demanded consumable items at the base-level. This investigation examined how the Standard Base Supply System currently addresses seasonally demanded consumable items and some alternative methods of addressing seasonally demanded consumable items in the SBSS. The alternative methods analyzed in depth were simple and Winters' seasonal exponential smoothing. and Box-Jenkins forecasting models.

This study found that items under study display some seasonal demand tendencies. The sample consisted of 12 out of 77 items identified as seasonal by Stock Control personnel at Langley AFB, VA. A graphical analysis showed stronger seasonal demand tendencies than did the autocorrelation function in which the correlations between demands one year apart are determined.

As was expected, the two seasonal models, Winters' exponential smoothing and Box-Jenkins better predicted demands for items under study than the SBSS model. Of 28 forecasts, Winters' exponential smoothing was best 13 times, while Box-Jenkins models were best 9 times.

The autocorrelation function could be used to test demand data for seasonality and flag items with seasonal demand patterns for special seasonal treatment, but this is not currently practical. Any useful effort to test all items loaded on the SBSS at a base would require demand data for each item for four or, preferably, more years. Any manual attempts to test items for seasonality would be impractical given the number of items in the average base supply account.

Among the recommendations given as a result of this study is the suggestion that additional work be done to facilitate basing demand forecasts on seasonal models where appropriate.